BEYOND WRONG TURNS

The Impact Of Lane-Level Guidance And Distraction On The Cognitive Mechanisms Of Navigation Errors

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Abstract

Navigation errors (missed, wrong, and risky turns) reflect cognitive failures that remain insufficiently understood in in-vehicle navigation. This thesis examines how level of map guidance detail and cognitive distraction shape these errors through the lens of situation awareness. In a 2×2 within-subjects simulator study (N=40), drivers completed four urban routes under Road-level versus Lane-level Navigation (LLN) guidance, with and without an auditory 2-back task. The study was conducted in collaboration with TomTom N.V., leveraging a simulator and eye-tracking system replicating their navigation application to investigate these effects. Multimodal data were collected, including vehicle control, eye movements, secondary task performance, and subjective workload and user experience ratings. Observed navigation errors were mapped to perception, interpretation, or decision-making failures in cognitive processes.

LLN significantly reduced interpretation failures and wrong turns, contributing to a 40% reduction in total errors. It also reallocated attention toward the navigation display, as shown by more frequent and longer glances and broader scanning, without degrading vehicle control. Distraction robustly elevated workload and reduced road monitoring, but session-level error rates remained unchanged. Interaction analyses showed that distraction attenuated LLN's attention-shift effects, while LLN mitigated some distraction costs in road monitoring; certain control benefits, however, reversed under load. Driver experience moderated outcomes: experienced drivers benefited consistently from LLN, with fewer errors and lower workload, while less experienced drivers reported higher workload and a tendency toward more missed turns.

Together, these findings demonstrate how navigation errors can be systematically mapped to underlying cognitive failures and reveal how level of map guidance detail and distraction influence these processes, providing a foundation for more context-aware navigation support.

Keywords

Navigation errors, Lane-level navigation (LLN), Driving simulator, Cognitive distraction, Eye-tracking, Situation awareness, Navigation System

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1. Introduction

Driving is a complex cognitive task that requires continuous attention, spatial awareness, and dynamic interaction with the driving environment. While substantial research has been devoted to understanding driving errors that directly contribute to crashes *(Khattak et al., 2021)*, there is a class of errors related to wayfinding that remains insufficiently explored *(Burns, 1998)*. These are known as "navigation errors", which include behaviors such as making wrong turns and missing exits *(Ege et al., 2011a)*. Unlike errors in vehicle control or operation, navigation errors are rooted in situational awareness, the comprehension of navigation cues, and decision-making under time constraints.

Despite the lack of direct statistics linking navigation errors to crashes, existing simulator studies have demonstrated the difficulties in wayfinding were associated with impaired driving performance and increased crash rates *(Wood et al., 2009)*. Navigation errors can also precipitate dangerous compensatory behaviors, such as abrupt lane changes or sudden braking when a driver is about to miss an exit, substantially increasing the risk of collisions *(Ucar et al., 2023)*. Therefore, addressing navigation errors is critical for enhancing wayfinding performance and overall road safety. Importantly, in-vehicle navigation system design can either mitigate or increase such errors. For example, a survey of in-car GPS users revealed that 82% had received inefficient route guidance, with 37% encountering dangerous inaccuracies *(Forbes & Burnett, 2008)*. By contrast, design factors such as optimized prompt timing have been shown to improve driving performance and reduce navigation errors *(Zhang et al., 2024)*.

While prior research has largely treated navigation errors as simple metrics for evaluating system usability or driver performance, few studies have systematically investigated the cognitive mechanisms underlying navigation errors. This study aims to fill this gap by focusing on two critical but insufficiently understood factors. First, although cognitive distraction is a known contributor to driving accidents *(National Center for Statistics and Analysis, 2025)*, its specific impact on the cognitive processes of wayfinding is not well explored *(Engström et al., 2017; Strayer et al., 2015)*. Second, lane-level navigation (LLN) is an emerging feature in in-vehicle navigation system that is worth examination. LLN provides guidance at the individual lane level, offering lane information about vehicle positioning, route visualization, and potentially real-time traffic or restriction data *(Winkler & Soleimani, 2025; Lee et al., 2015; Song et al., 2017)*. While LLN is expected to improve user experience and road safety by providing more detailed driving context, the implication of its human-machine interface (HMI) needs further evaluation. Specifically, how detailed visual information of LLN affects navigational performance, visual attention and cognitive load, remains a significant research gap. This issue is especially important as a navigation system itself is a source of distraction: in 2017, 2,732 fatalities were caused as a result of in-vehicle distractions other than cellphone use *(Yared et al., 2020)*. Understanding how LLN interacts with distraction is therefore a critical question for future research.

This study was conducted in collaboration with TomTom N.V., a navigation and geolocation technology company with interest in enhancing navigation experiences and safety through intelligent maps. TomTom is currently rolling LLN as a product feature in their navigation products. Given this context, this study systematically investigates the interplay between the level of map guidance detail and cognitive distraction and to uncover how these two factors influence the underlying cognitive failures that precipitate navigation errors.

In this study, we evaluated and compared the two levels of map guidance (Basic road-level navigation and enhanced lane-level navigation) under the same navigation system user interface framework. As shown in Fig.1, road-level navigation presents a map with a lower zoom-level, showing a big picture of a planned route while lane-level guidance presents a map with a higher zoom-level, showing lane information under more detailed route context. Notably, lane-level guidance maintains the same low zoom-level as road-level guidance by default, but automatically zooms in to lane-level when approaching the intersections. The design of the UI is a replication of TomTom's Automotive Navigation Application *(Navigation SDK for Automotive, n.d.)* and styling of map is a modification of TomTom's premium 3D map display. The camera behaviors are detailed by section 4.2.

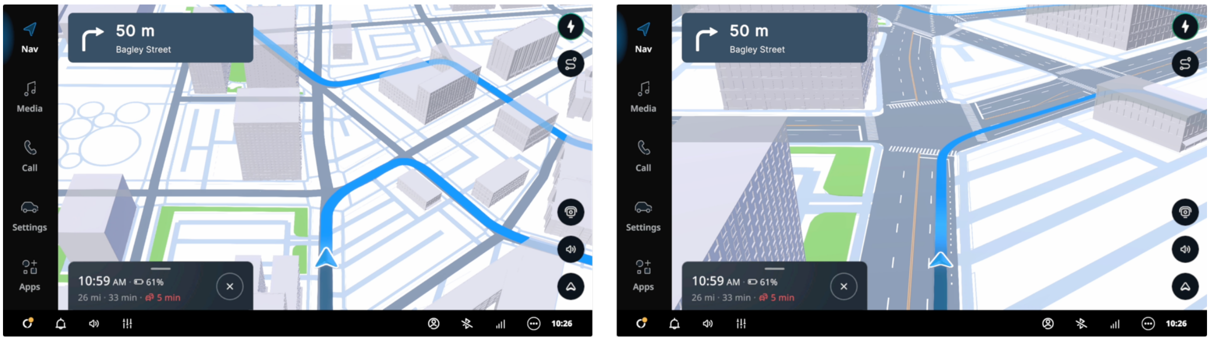


Fig. 1 Two levels of map guidance: Basic road-level navigation (left) and Enhanced lane-level navigation (right)

To conduct this research, we employed a driving simulator study combined with eye-tracking technology to observe and analyze driver behavior. The simulator provides a safe, controlled environment to replicate real-world driving scenarios *(Meuleners & Fraser, 2015)*, while the eye-tracking data allows us to investigate drivers' visual attention and cognitive processes *(Liu et al., 2024)*. This multi-modal approach not only enables us to observe errors at the behavioral level but also provides insights into the underlying cognitive mechanisms responsible for these errors, such as failures in perceiving a navigation cue, misinterpreting its meaning, decision-making processes that allow for timely and safe maneuver. The simulator cockpit and the driving task simulation software, both developed by the UX Team, are located at TomTom's Amsterdam office and have been adapted for the purposes of this study.

The findings of this study hold the potential to inform the design of safer, more effective and intuitive in-vehicle navigation systems. By addressing the gap in insufficient understanding of navigation errors and their cognitive mechanisms, along with emerging contributing factors like LLN, this research aims to enhance driving safety and advance human-machine interface design.

2. Background

2.1 Defining and Classifying Navigation Errors

While "driving errors" such as inadequate surveillance, speeding, and improper maneuvers have received considerable attention in past studies *(Khattak et al., 2021; Papantoniou et al., 2019)*, the concept of "navigation errors" has not been consistently defined across the literature. Existing studies adopt varied, context-specific definitions, typically describing behaviors such as "taking a wrong turn," "missing a turn," or "following the wrong route" *(C.-T. Lin et al., 2010; Yared et al., 2020; L. Yang et al., 2021)*. Unlike driving errors, navigation errors are associated with failures in wayfinding, spatial awareness, or the interpretation and response to navigation instructions *(Burns, 1998; Ucar et al., 2023)*.

This study defines navigation errors conceptually as deviations from a planned route while following navigation *(Morris et al., 2024)*. Operationally, we classify these errors into three categories: (1) missing a turn or exit, (2) taking an incorrect turn or exit *(Ege et al., 2011a; C.-T. Lin et al., 2010; Burns, 1998)*, and (3) making a risky corrective turn, such as an abrupt maneuver to avoid or correct a potential error *(Morris et al., 2024; Ucar et al., 2023)*. Risky turns can be viewed as compensatory behaviors triggered when drivers attempt to avert missed or wrong turns, as well as incorrect judgement and decision in forcing a turn despite insufficient time or space. Such actions have been linked to severe and fatal crashes *(Ucar et al., 2023)*. Furthermore, both missed turns and wrong turns can negatively affect driving safety, efficiency and vehicle control stability *(Zhang et al., 2024)*.

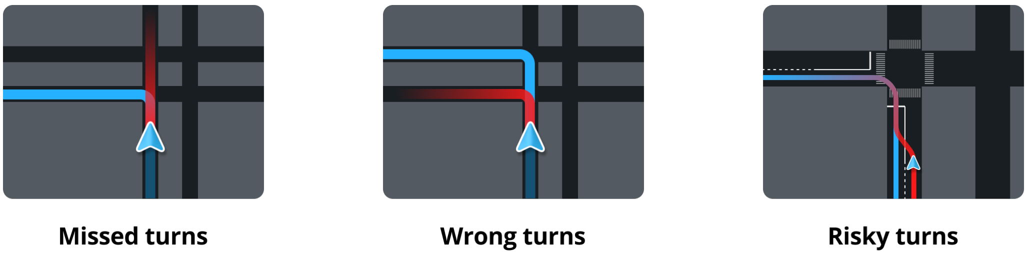


Fig. 2 Visualization of 3 types of navigation errors: Blue routes show intended maneuvers and red routes show actual maneuvers that lead to navigation errors

2.2. A Theoretical Framework for Cognitive Failures in Driving

To understand how and why navigation errors occur, this study is grounded in Endsley's model of Situation Awareness (SA), a framework well-suited to this purpose *(M. R. Endsley, 1999)*. SA is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" *(M. R. Endsley, 1988)*. The model delineates three hierarchical levels of cognitive processing that are crucial for effective performance in dynamic and complex environments like driving. Failures in SA can be categorized according to these three levels, providing a structured approach to analyzing operator errors.

Under the context of driving with a navigation interface, we adapted three levels of SA failures in Endsley's model into a taxonomy of cognitive failures, which directly led to the navigation errors observed in our experiment.

(1) Level 1: Perception Failure. This corresponds to failures in the initial stage of SA, where an individual fails to perceive crucial information from their environment. In driving scenario, this is where the driver fails to notice or become aware of a navigation instruction. The underlying causes can be diverse, ranging from a failure to monitor the navigation display due to distraction or limited attention *(C.-T. Lin et al., 2010)*, to navigation cues being hard to detect *(Burns, 1998)*, to a misperception of the cue, or a memory loss that causes a correctly perceived instruction to be forgotten *(Bian et al., 2021)*.

(2) Level 2: Interpretation Failure. This level relates to failures in comprehending the significance of perceived information. This is where the driver observes a navigation instruction but fails to correctly process or understand its meaning within the current driving context. Such failures might stem from a lack of a mental model where the driver does not understand the navigation cues *(L. Yang et al., 2021)*, or the use of an incorrect mental model where the driver misinterprets the cue of a complex intersection *(Morris et al., 2024)*. It can also occur when drivers rely on past driving experience or habitual responses rather than the immediate navigation cues, such as wrongly applying familiar route patterns to a new situation.

(3) Level 3: Decision-making Failure. The highest level of SA involves projecting the future state of the environment to make timely and effective decisions. Here, the driver correctly perceives and interprets the navigation cue but fails to execute the appropriate maneuver safely or effectively. This can be caused by a failure to project the time and steps required for a safe lane change *(Ucar et al., 2023)*, or by an over-projection of current trends, such as failing to decelerate appropriately before a turn, leading to risky last-second actions.

By mapping observable driving and gaze behaviors to this three-level framework, this study aims to diagnose the underlying cognitive breakdowns that precipitate them.

2.3 Factors Influencing Navigation Errors

Previous research has identified several key factors that contribute to the occurrence of navigation errors. One important aspect of factors relates to the design of navigation systems. The timing and content of navigation instruction critically influence driver performance. Early or delayed prompts impair efficiency and safety, while tailored messages enhance preparedness and reduce cognitive load *(L. Yang et al., 2021)*. Map display size impacts distraction and driving performance, with larger screens reducing navigation errors *(Yared et al., 2020)* and sub-windows improving guidance as well increasing visual demands. No significant differences were found between 2D and 3D e-maps, though poorly designed 3D maps can lead to more frequent glances. *(C.-T. Lin et al., 2010)*. Beyond visual information, human–machine interface (HMI) modalities such as haptic feedback also influence performance. For example, vibrotactile cues in steering delivered through the steering wheel reduce cognitive load and navigation errors, especially in noisy environments *(Ege et al., 2011a)*.

Roadway complexity also strongly affects wayfinding performance. Drivers encounter elevated cognitive load at complex intersections such as J-turns *(Morris et al., 2024)*, F-type intersections *(L. Yang et al., 2021)*, and multi-exit expressways *(Bian et al., 2021)*, leading to navigation errors and risky maneuvers *(Jalayer et al., 2016)*. Similarly, navigation errors are more frequent in urban areas than rural areas, with the same GPS display *(Yared et al., 2020)*.

Individual driver characteristics significantly shape vulnerability to navigation errors. Older drivers *(Bryden et al., 2023; Forbes & Burnett, 2008; Read et al., 2011)* and drivers with cognitive impairments, such as Parkinson's disease *(Uc et al., 2007)* are more likely to commit more navigation errors due to declines and cognitive and visual function. More years of driving experience were found associated with improved driving safety for young drivers *(Yared et al., 2020)* while navigational expertise associated with better wayfinding performance in unfamiliar environments*(Woollett & Maguire, 2010)*. Distraction also plays a critical role: engaging in secondary tasks, including cell phone use or passenger interaction, diverts attention from the primary driving task and increases navigation errors *(Papantoniou et al., 2019)*.

Building on this foundation, this study focuses on two factors that may contribute to navigation errors during driving: cognitive distraction and lane-level navigation (LLN) display. Cognitive distraction is well known to impair driving performance and road safety, yet its specific effect on the cognitive processes of wayfinding remains less understood. LLN, in turn, represents a growing trend in navigation system design, offering granular, lane-specific guidance that promises to enhance wayfinding and user experience. However, little is known about the human–machine interaction implications of LLN on standard in-vehicle displays, particularly when drivers are operating under elevated cognitive load. To address these research gaps, this study systematically investigates how these two factors interact to influence the underlying cognitive failures that lead to navigation errors, with the goal of informing the design of safer and more effective navigation systems.

Beyond these two primary variables, exploratory analyses also examine the potential influence of driving experience (Section 6.5) and intersection complexity (Section 6.6.2) on cognitive processes related to navigation errors.

2.4 In-Vehicle Navigation Systems

2.4.1 Navigation Guidance

In-vehicle navigation systems have become ubiquitous, yet their design significantly impacts driver safety and performance *(L. Yang et al., 2021)*. Inefficient interfaces can lead to navigation errors, such as missed turns, particularly at complex intersections*(Suzuki & Moriya, 2024)*. Research indicates that factors like display size are critical, with smaller screens correlating with a higher number and longer duration of errors due to increased time needed to retrieve information *(Yared et al., 2020)*. Likewise, the timing and content of prompts are crucial;

instructions that are delivered too early, too late, or are difficult to understand can negatively affect driving efficiency and stability (L. Yang et al., 2021).

The modality used to deliver guidance has an important effect on the drivers. Visual displays, such as 2D or 3D maps, carry a significant "visual cost," requiring drivers to shift their gaze from the road. This can compromise attention and vehicle control (P.-C. Lin & Chen, 2013). In contrast, auditory (voice-guided) instructions generally impose a lower cognitive workload and are considered safer, as they reduce visual demand (Zhong et al., 2024). However, their effectiveness can decrease with complexity, as compound auditory instructions can interfere with driving performance (Suzuki & Moriya, 2024). While many systems are multimodal (combining visual and auditory outputs), emerging research also explores tactile and gesture-based interfaces to further reduce cognitive load.

A central issue with navigation system use is driver distraction, as secondary task like wayfinding might divert attention away from driving task (Bryden et al., 2023). Visual-manual interactions are a major safety concern, significantly increasing crash risk by causing drivers to take their eyes off the road (Zhong et al., 2024). The duration of these glances is a key predictor of risk, with looks away from the road longer than 1.6 seconds being strongly associated with crashes or near-crashes (Zhong et al., 2024). When the cognitive demands imposed by the system exceed the driver's processing capacity, it can lead to cognitive overload, resulting in slower reaction times and impaired vehicle handling.

Given the significant and well-documented safety risks associated with visual distraction from in-vehicle displays, this study deliberately focuses exclusively on the visual modality. By isolating the visual modality, the research can conduct a controlled investigation into how different levels of visual information detail (road-level vs. lane-level) impact cognitive failures and driving performance. Therefore, other modalities, such as auditory or haptic feedback, are considered out of the scope of this study.

2.4.2 Lane-Level Navigation

Lane-level navigation represents a significant advancement over traditional road-level guidance, providing drivers with precise instructions about which lane to be in for upcoming maneuvers. Its core functionality involves determining lane changes or departures based on real-time route information, road properties, driving lane details, and precise vehicle positioning (Lee et al., 2015). Visualization of such lane guidance can be a highly efficient way to provide navigation instructions, particularly in situations where being in the wrong lane can lead to negative consequences such as missed turns or dangerous late merges. This level of detail is critical for the development of Advanced Driver-Assistance Systems (ADAS) and autonomous vehicles, as it enables safer and more efficient path planning, particularly in complex urban environments and at challenging intersections (Zheng et al., 2019).

The foundation of lane-level navigation lies in High-Definition (HD) maps, which model the road network with decimeter-level accuracy (Betaille & Toledo-Moreo, 2010). A substantial body of research has focused on the creation and maintenance of these maps, developing sophisticated techniques for generating lane-level geometry from various sensors and ensuring the data remains up to date. By contrast, research into the Human–Machine Interface (HMI) for LLN is less developed. Existing work has predominantly focused on Augmented Reality (AR) Heads-Up Displays (HUDs), which integrate guidance directly into the driver's forward view *(Bauerfeind et al., 2021)*. Studies in this area suggest that AR HUDs can reduce cognitive load, improve response times, and increase driver confidence by making lane-specific instructions more intuitive and reducing the mental effort required to translate abstract guidance into real-world action.

However, detailed visual guidance can also compromise lane-keeping and road safety when presented on displays that require drivers to glance away from the road. Interacting with console-mounted navigation systems has been shown to increase visual distraction, reduce forward-road glance time, and degrade lane-keeping performance, as indicated by greater lane position variability *(Kun et al., 2009)*.

This presents a critical research gap: most vehicles in use today still rely on standard console-mounted or personal navigation displays rather than AR HUDs, yet the effect of providing detailed LLN information on such secondary screens remains poorly understood. This interface paradigm introduces a trade-off. On the one hand, LLN has the potential to improve wayfinding efficiency and reduce navigation errors by offering clearer, lane-specific guidance. On the other hand, the costs of increased visual distraction from more frequent or longer glances away from the road may offset these benefits.

Therefore, this study investigates the impact of lane-level navigation presented on a standard navigation screen, exploring its influence on cognitive failures and driving performance.

3. Methodology

3.1 Cognitive Distraction and N-back Task

To investigate the effects of cognitive distraction, this study required a secondary task that could reliably manipulate cognitive load without interfering with the primary driving task's visual or behavioral demands. The n-back task was selected for this purpose due to its established effectiveness and validity in cognitive and driving research. The task is a continuous working memory task: participants are presented with a sequence of stimuli (e.g., numbers) and must indicate whether the current stimulus matches the one presented 'n' items earlier. By systematically varying the value of 'n', the task diverts processing and storage resources from the working memory system, allowing for controlled manipulation of cognitive load.

The n-back task's validity as a tool for inducing cognitive load in drivers is supported by a robust body of literature. Early research established the auditory n-back task as an effective method for elevating cognitive workload and measuring its effects on driver physiology, attention, and performance *(Mehler et al., 2011)*. Its distracting effects have been shown to manifest in degraded vehicle control, such as impaired speed management in curves *(Fu et al., 2019)*, and in altered gaze behavior *(S. Yang et al., 2018)*. A subsequent meta-analysis by von Janczewski et al. *(2021)*, confirmed that the n-back task has a "substantial effect on cognitive workload while driving," making it a suitable and powerful method for inducing and studying driver distraction.

A key advantage of the n-back task is its ability to isolate cognitive distraction. By implementing an auditory version with tactile responses (steering wheel buttons), as was done in this study, visual and manual interference with the primary driving task is minimized *(Nilsson et al., 2018)*. Furthermore, the n-back task provides a direct, objective measure of a driver's cognitive state. Performance metrics such as accuracy and response time serve as reliable indicators of processing efficiency and the cognitive resources available to the driver *(Strayer et al., 2015)*. High performance suggests sufficient capacity to manage multitask loads*(S. Yang et al., 2022)*, whereas low performance indicates heightened cognitive workload and impaired processing efficiency *(Strayer et al., 2015)*.

It is important to interpret these performance metrics within the context of a dual task driving scenario. The cognitive control hypothesis *(Engström et al., 2017)* provides a useful framework, suggesting that cognitive load selectively impairs tasks that require active cognitive control while leaving more automatic behaviors unaffected. In this study, this implies that a driver's performance on the n-back task reflects not only the cognitive load imposed by the task itself but also the driver's strategic allocation of mental resources. A decline in n-back performance may therefore represent a deliberate shedding of the secondary task to preserve capacity for the primary driving task.

3.2 Driving Simulators in Driving Behavior Research

Driving simulators are valuable tools in driving research because they provide a safe, controlled environment to study situations that would be too dangerous or impractical on the road *(Meuleners & Fraser, 2015)*. This control allows researchers to create repeatable experimental conditions to test driver behavior, including traffic, distractions and in-vehicle systems *(Knapper et al., 2015)*.

A key concern is the validity of simulator findings in comparison with real-world driving. Research distinguishes between two types: Absolute validity means that measures like speed are identical to on-road driving. Relative validity means that the patterns of behavior are the same, such as distraction causes similar effects in both the simulator and reality *(Knapper et al., 2015)*, which is adopted for this study. The degree to which a simulator emulates real-world driving is known as fidelity, including physical, visual, and motion dimensions. The simulator used in this study is considered low fidelity, based on the classification by Wynne et al. *(2019)*, featuring a fixed base, limited screen view but realistic physical controls. However, research has shown that the relationship between fidelity and study validity is not always direct; the simulator's capabilities must simply be appropriate for the research questions.

Specifically for navigation research, simulators show promising but mixed results. Studies have successfully used them to replicate real-world wayfinding errors, such as taking a wrong turn, demonstrating their relative validity for such tasks *(Knapper et al., 2015)*. However, another study indicates that simulators may not always predict a driver's specific orientational performance, due to lower orientation demands in simulated tasks than in the real world *(Faschina et al., 2021)*. Therefore, while simulators are a powerful methodology for this study, the task design was developed to ensure high navigational demands, and the findings must be interpreted with these considerations in mind.

3.3 The Use of Eye-Tracking in Driving Studies

Eye-tracking is an essential tool in driving research as it offers an objective, quantitative window into a driver's visual attention and cognitive processes *(Liu et al., 2024)*, providing significant potential to enhance driving safety, assess workload, and evaluate driving behavior *(Zang & Liu, 2012)*. Based on the "eye-mind hypothesis," which posits a strong link between where a person is looking and what they are thinking about *(Cabrall et al., 2018)*, eye-tracking allows researchers to infer a driver's focus of attention and information gathering strategies. Eye-tracking metrics analyzed in this study is guided by ISO 15007:2020 *(International Organization for Standardization (ISO), 2020)*:

Fixation (100-2000 ms): When the eyes pause to process information, with longer durations indicating more complex cognitive processing.

Saccades (20-100 ms duration, 1-5° amplitude): Rapid movements between fixations, with larger amplitudes indicating broader visual scanning.

Glance (500ms-3000s)**:** Temporal maintaining of visual gaze within an area of interest (AOI), which may include multiple fixations and saccades. Glance duration over 2 seconds is considered dangerous for driving.

Pupil dilation (2-8 mm diameter): Can indicate changes in cognitive load, with larger pupils suggesting increased mental effort.

Blink rate (0.1-0.5 blinks/sec, normal blink ≤300 ms): Normally decreases under high cognitive load as attention is focused on the task.

In driving studies, these metrics are often measured in relation to specific AOIs and then widely used to understand driver attention and cognitive processes. For example, fixations reflect the amount of information processed from AOI and are critical for anticipating upcoming turns and guiding driving actions *(Castro, 2009)*. Dwell time, defined as the cumulative time spent fixating on an AOI, serves as a marker of attention distribution across different AOIs *(Ayiei, 2020)*. Saccades, the rapid eye movements between different AOIs, help maintain correct fixation while driving *(Guidetti et al., 2019)*. Blink rate, blink duration and pupil dilation are commonly used as indicators of cognitive load, with changes reflecting variations in mental effort *(Yuen et al., 2021)*. Eye-tracking data can further evaluate the usability of in-vehicle systems *(Baldisserotto et al., 2023)*, and even predict driver maneuvers like turns or lane changes.

For this study, eye-tracking is indispensable for moving beyond classifying what navigation errors occur to understanding why and how they occur. However, interpreting this data is complex, as eye-tracking measures overt visual attention but does not directly reveal cognitive processing *(Ahlström et al., 2021)*. For instance, a driver fixating on the navigation display does not guarantee they understood the instruction *(Chen, 2024)*. To overcome this limitation, this study integrates eye-tracking metrics with driving performance data (e.g., steering angle, speed; *(Pan et al., 2022)*) and subjective workload measures like NASA-TLX *(Nakayama et al., 2024)*, a practice supported by the literature. This data fusion is critical for mapping observable behaviors to the theoretical framework of cognitive failures *(Ringhand et al., 2022)*. For example:

- A perception failure may be inferred if a driver fails to fixate on the navigation display prior to an intersection.
- An interpretation failure may be identified when a driver fixates on the navigation guidance but still executes an incorrect maneuver.
- A decision-making failure may be evidenced by late or rapid glances to the display, indicating a failure to project and plan the maneuver in time.

By triangulating gaze patterns, vehicle data, and subjective reports, this study can draw more reliable conclusions about the driver's cognitive processes *(Ahlström et al., 2021)*. This multi-modal analysis allows the study to directly test its hypotheses. For instance, gaze concentration, a known effect of cognitive load, can be measured to see if it causes more perception failures *(Ringhand et al., 2022)*. This detailed understanding of driver behavior provides a basis for designing safer, more intuitive navigation interfaces and creates opportunities for future systems that could predict and mitigate navigation errors before they happen.

4. Navigation System Prototype

4.1 Navigation User Interface (UI)

The user interface used in the study is a replication of TomTom's established product, navigation UI embedded in Navigation SDK *(Navigation SDK for Automotive, n.d.)*, which serves as a baseline for evaluating the effects of two levels of map guidance. As is shown in Fig3, the UI is divided into several functional areas:

1. **Manual interaction buttons (left column, right column and bottom bar)**: These buttons are designed for advanced in-vehicle entertainment features, such as listening to music. However, they are non-interactive in this study and are retained solely for the purpose of simulating a realistic environment.
2. **Route overview (bottom left)**: This area is intended to inform the drivers of the current time, distance to destination and estimated arrival time. In this study, only a placeholder is included, as all routes are relatively short.
3. **Navigation header (top left)**: This section provides information regarding the next maneuver, including an icon representing the upcoming action (e.g., left turn, right turn, U-turn); the distance to the next maneuver; the name of the street to be entered. This feature is enabled for the study.

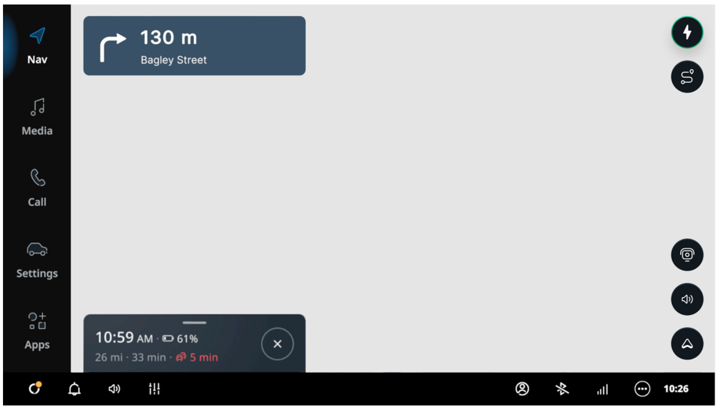


Fig. 3 User interface of navigation app employed by the study

4.2 Map Visualization

Map visualization, as the primary focus of this study, occupies most of the screen, where we replicated TomTom's premium map display using Unity. The map features 3D renderings of buildings on map, aimed at providing better representation of the real world and improving drivers' understanding of an environment *(Gardony et al., 2022)*.

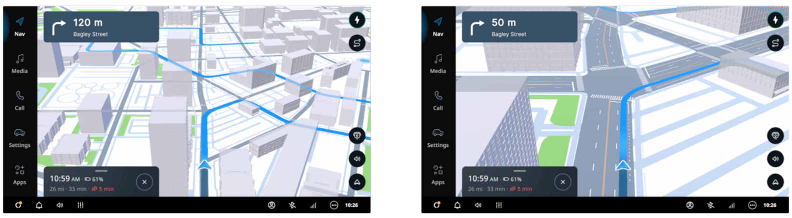
In this study, we evaluated and compared two levels of map guidance within the same map visualization style and navigation UI framework. Enhanced road-level navigation provides an overarching view of the route, which is crucial for overall situational awareness. In contrast, lane-level navigation offers detailed lane information as drivers approach intersections, addressing the specific demands of complex maneuvers. The camera behaviors of the map display are guided by TomTom's general specifications:

1. **Road-level Navigation**: This mode features a lower zoom level across the route (zoom level 0 represents the whole world, with increased zoom level showing closer views of the environment), providing a broader perspective. Between 125 and 100 meters prior to a maneuver, the camera tilts upward, transitioning the display from a bird's-eye view to a more angled, forward-looking view as shown in Fig4(b). Between 75 and 50 meters prior to a maneuver, the camera zooms in slightly while maintaining a road-level visualization as illustrated in Fig4(c). The tilt angle further increases during this phase. After the turn, the camera reverts to its default view, as shown in Fig4(a), unless the distance to the next turn is smaller than 125 meters; in this case, the view remains active.

(a) (b) (c)

Fig. 4 Camera behavior changes under road-level guidance: (a) 150m prior to a maneuver;(b) 125m prior to a maneuver; (c) 50m prior to a maneuver

2. **Lane-level Navigation**: This mode incorporates a higher zoom level when approaching intersections, providing detailed lane information. Between 125 and 100 meters prior to a maneuver, the camera gradually zooms in to a closer, lane-level perspective, as illustrated in Fig5(b). In this view, the tilt angle remains constant, and the system provides lane-specific guidance by highlighting the appropriate lane for the upcoming maneuver and rendering key road markings on the map display. After the turn, the camera reverts to its default road-level view, as shown in Fig5(a), unless the distance to the next turn is smaller than 125 meters; in this case, the lane-level view remains active.



(a) (b)

Fig. 5 Camera behavior changes under lane-level guidance: (a) 125m prior to a maneuver; (b) 50m prior to a maneuver

It’s expected that in complex urban environments with more frequent and complex intersections, detailed lane level information will enhance interpretation of the map and thus improve navigation performance. To investigate this hypothesis further, it is important to note that the navigation system prototyped in this study provides visual cues only, with no auditory guidance. This design choice emphasizes the study's objective, which is to understand visual attention under the two levels of map guidance.

5. Study

5.1 Research Questions

This study was guided by two primary research questions and a set of corresponding hypotheses.

RQ 1: How can navigation errors (missed turns, wrong turns, risky turns) be classified and mapped to underlying cognitive processing failures such as perception, interpretation, or decision-making failures?

This exploratory question aimed to build a conceptual mapping based on the following theoretical assumptions, which define the cognitive failures of interest:

> **Perception Failure:** The driver failed to notice or become aware of the navigation instruction. We hypothesize this is the primary cause of missed turns.
>
> **Interpretation Failure**: The driver noticed the instruction but failed to correctly process or understand its meaning. We hypothesize this is the primary cause of wrong turns.
>
> **Decision-making Failure:** The driver understood the cue but responded too late or executed a risky maneuver. This is expected to be associated with risky turns.

RQ 2: How do cognitive distraction and the level of map guidance detail (road-level or lane-level) at urban intersections influence the occurrence of these cognitive processing failures and associated navigation errors?

This question is addressed through the following hypotheses:

> **H1**: Drivers under cognitive distraction will experience more perception failures, leading to a higher frequency of missed turns, compared to drivers without distraction.
>
> **H2**: Lane-level navigation guidance at intersections will decrease interpretation failures, leading to fewer wrong turns, compared to road-level guidance, particularly in complex intersection scenarios.
>
> **H3**: Lane-level navigation guidance at intersections will decrease decision-making failures, leading to fewer risky turns, compared to road-level guidance, particularly in complex intersection scenarios.
>
> **H4**: Lane-level guidance will partially mitigate the negative effects of cognitive distraction by reducing interpretation failures and decision-making failures but will not significantly reduce perception failures caused by distraction.

5.2 Experimental Design

The study employed a 2 (Cognitive Distraction: Present vs. Absent) × 2 (Level of Map Guidance Detail: Road-level vs. Lane-level) within-subjects design. Each participant experienced all four experimental conditions. The order of conditions was counterbalanced across participants to control learning and fatigue effects.

Independent Variables:

1. **Cognitive Distraction**: This was manipulated using an auditory 2-back task (Present) versus no secondary task (Absent).
2. **Level of Map Guidance Detail**: This was manipulated by providing either standard Road-level guidance all the way or enhanced Lane-level guidance at intersections.

Dependent Variables:

- **Navigation Errors**: Classified as missed turns, wrong turns, and risky turns based on driving behavior *(Ege et al., 2011b; Morris et al., 2024; Read et al., 2011)*.
- **Cognitive Failures**: Classified as perception failure, interpretation failure, and decision-making failure. Inferred from participant self-reports, and supported by eye-tracking data (e.g., fixations on navigation display) and driving behavior *(Ahlström et al., 2021; M. R. Endsley, 1999)*.
- **Gaze Behavior**: Eye-tracking data was processed to extract key metrics related to visual attention and cognitive load, including fixation, saccades, blinks, and pupil dilation *(Zang & Liu, 2012; Kapitaniak et al., 2015; Yared et al., 2020)*.
- **Driving Behavior**: Including vehicle speed, steering angle, brake and accelerator pedal behavior, lane deviation *(Bian et al., 2021; Dalton et al., 2013; Suzuki & Moriya, 2024)*.
- **Subjective Workload**: Measured using the NASA-TLX questionnaire *(Nakayama et al., 2024; Wen et al., 2024; Zhong et al., 2024)*.
- **User Experience**: Measured using the User Experience Questionnaire (UEQ).

5.3 Participants

A total of 40 participants (31 males, 9 females) were recruited from TomTom employees without prior knowledge of this study. The age of participants ranged from 18 to 64 years, with the majority (82.5%) falling between 25 and 44 years old. All participants held a valid driver's license for an average of 12.31 years (SD = 7.97 years) and had normal or corrected-to-normal vision.

To examine the role of driving experience, participants were categorized into two groups: more experienced drivers (n = 23), who reported driving at least once per week, and less experienced drivers (n = 17), who drove less frequently. This classification followed the similar criteria used in previous study *(Inagaki et al., 2020; Nobukawa et al., 2021)*. Additionally, 18 participants had prior experience with driving simulators or racing games, while 22 had no such experience.

5.4 Apparatus

The experiment was conducted in an office setting with consistent lighting, using a fixed-base driving simulator with the following components:

Physical Cockpit and Displays: The simulator cockpit is constructed with car interior and a metal frame that did not include view-obstructing elements like A-pillars. It featured an adjustable driver's seat (base height 50 cm) to accommodate different participants. Participants were seated at approximately 175 cm from the forward road view displayed on a 65-inch NEC C651Q screen (3840×2160 at 30 Hz, 16:9, HDMI). A secondary 15.6-inch ASUS MB16AC screen (1920×1080 at 60 Hz, 16:9, DisplayLink USB) displaying the navigation view was positioned 10 cm to the right of the steering wheel, mimicking the standard central stack display in cars. This placement resulted in a viewing distance of approximately 75 cm from the participant's eyes to the navigation screen.

Fig. 6 Physical set up of the driving simulator

Simulation Software: The driving simulation was developed in Unity 6000.0.23f1 *(Unity, 2024)* and built for Windows 11 Enterprise 64-bit (build 26100) using the DirectX 12 graphics backend on an NVIDIA GeForce RTX 3080 GPU (10 GB VRAM) with an Intel Core i9-10900 CPU and 64 GB RAM. The software rendered a high-fidelity 3D scenario that represented a realistic urban environment, as illustrated in Fig7. The city environment was originally developed by UX designers at TomTom and further adapted for this study by the researchers. Besides an urban environment, the road view screen also includes (1) rearview mirror, following the approach of Morris et al. *(2024)*; (2) current vehicle speed value that turns red outside the range of 20–60 km/h, with similar approach utilized in C.-T. Lin et al. *(2007)* and Ma & Kaber as was incorporated in *(2010)*; (3) a 5-minute timer to suggest the driver to drive with proper speed. These features are designed to help participants maintain proper driving speeds in the city environment.

Navigation displays were rendered using the same scene but with different camera behaviors and visualization styles, as described in Section 4.2. Driving data were logged using custom C# scripts within the Unity project.

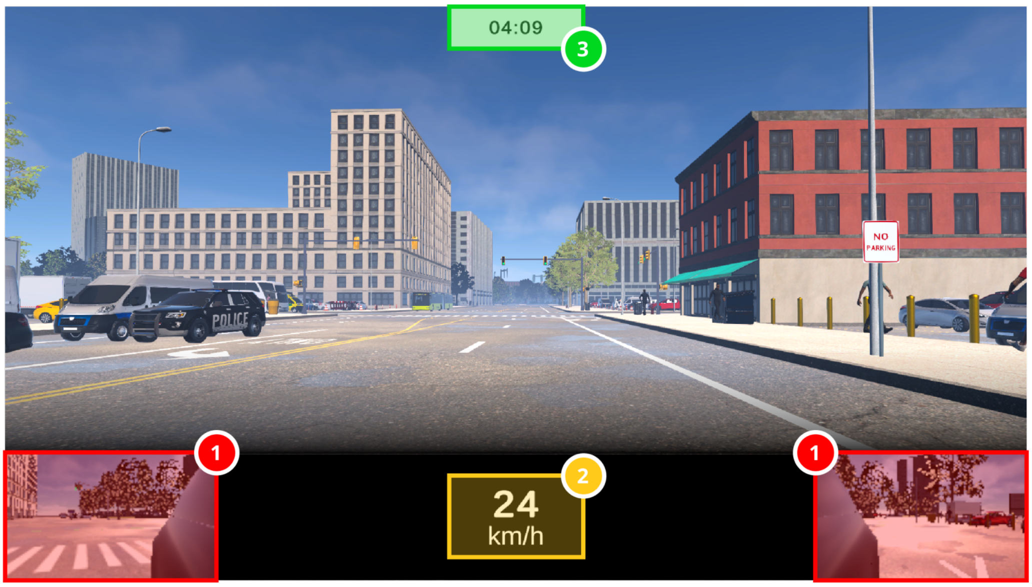


Fig. 7 Screenshot of the road view screen

Driving Controls: A Fanatec steering system was used to capture steering, acceleration, and braking inputs. The setup included a ClubSport Steering Wheel Classic 2 V2 mounted on a ClubSport Universal Hub V2 with Button Module Endurance, connected to a Fanatec wheelbase; the Fanatec PC driver was v8.20.0005.0600. Firmware versions: Wheel Base Motor Firmware 1.0.3.2, Wheel Base Firmware 1.5.0.1, Wireless Quick Release Firmware 6.0.1.1 (all up to date). The pedal set was CSL Pedals. Any of the 12 buttons on the steering wheel, as shown in Fig.9, could be used to respond in the n-back task.

Eye-Tracker: A Pupil Labs Neon wearable, glasses-based eye-tracker *(Baumann & Dierkes, 2023)* was used to record binocular gaze at 200 Hz. Data were captured using the Neon Companion app (2.9.8-prod) running on a OnePlus 8T (Android 11). The Neon module firmware was v24.8 with pipeline v2.8.0. The eye-tracker was calibrated prior to each session following the manufacturer's procedure.

5.5 Task and Stimuli

Participants drove four predefined routes in a simulated urban environment based on real map data from Detroit, USA, to ensure unfamiliarity. Each route was approximately 1.8 km long (approx. 4 minutes driving time) and included 12 intersections requiring a maneuver (left, right, or U-turn). Several of these intersections were designed with higher complexity to induce navigation errors. See Appendix1 for detailed route information.

(a) Route A **(b) Route B**

(c) Route C **(d) Route D**

Fig. 8 Four routes tested in the study

The route design followed established protocols in driving simulator research. Route length and duration (1.6–2.0 km; 3–4 minutes) are commonly used in urban driving studies *(Papantoniou et al., 2019; Ringhand et al., 2022)*, balancing ecological validity with experimental control while minimizing fatigue. Similarly, the use of 12 intersections (~1 every 150 m) provided sufficient opportunities to observe navigation behavior without overwhelming participants, aligning with prior studies that employed 5–10 intersections per route *(Ringhand et al., 2022; Schoemig et al., 2018)*.

The simulated environment included standard road markings such as lane divisions, crosswalks, and turning arrows on the road surface. However, to focus the driver's task on interpreting the navigation system, certain real-world elements were deliberately omitted. There was no same-direction traffic, no pedestrians crossing the driver’s path, and all traffic lights were set to green. Vertical traffic signs for lane guidance were also removed, and participants were not required to use turn signals. While reducing the simulation's ecological validity, these choices were made to isolate the cognitive tasks of interest and increase the likelihood of navigation errors directly related to the on-screen navigation guidance.

During the cognitive distraction conditions, an auditory 2-back task was performed concurrently with the driving task. Participants listened to a sequence of spoken digits, presented at a consistent interval of 3 seconds, and were instructed to press buttons on the steering wheel when the current digit matched the digit presented two digits earlier in the sequence. Participants could use any of the 12 buttons on the steering wheel to report a match.

Fig. 9 A participant is pressing a button on the steering wheel (left); steering wheel utilized in the study (right)

The task was algorithmically controlled to maintain a consistent level of cognitive load. The stimulus sequence was structured to have an overall target match frequency of approximately 30%. To prevent pattern recognition and maintain engagement, the sequence was constrained to a maximum of two consecutive matches and six consecutive non-matches. Participant responses were logged and classified as hits, false alarms, or misses to provide performance metrics for the secondary task.

To isolate the effects of the independent variables while maintaining a baseline of realism, the driving environment was highly controlled. The weather was consistently clear and sunny, and all roads were flat. To increase immersion, non-conflicting vehicles were present on parallel roads and pedestrians were visible on sidewalks, but neither would ever intersect the participant's path. All traffic lights encountered by the participant were green. The auditory environment consisted of low-volume vehicle engine and movement sounds, supplemented by the spoken digits of the 2-back task during distraction conditions.

5.6 Procedure

Participants first received a briefing, provided informed consent, and completed a demographics questionnaire. After calibration of eye, a short practice drive was conducted to familiarize the participant with the simulator, the two levels of map guidance detail, and the 2-back task.

Each participant then completed four experimental drives. To mitigate order effects from both route sequence and experimental conditions, Latin square design was applied. The 40 participants were divided into eight groups of five, with each group following a unique sequence. The 40 participants were divided into eight groups of five, with each group assigned a unique drive sequence. This design ensured that every pairing of route (A, B, C, D) and condition (1–4) was experienced by 10 participants, balancing potential route-specific influences across the dataset.

Condition 1: No distraction with Road-level guidance

Condition 2: No distraction with Lane-level guidance

Condition 3: Distraction with Road-level guidance

Condition 4: Distraction with Lane-level guidance

Table 1 Grouping of participants for experiments

Group	1^{st} Round	2^{nd} Round	3^{rd} Round	4^{th} Round
1	Route A, Condition 1	Route B, Condition 2	Route C, Condition 3	Route D, Condition 4
2	Route B, Condition 3	Route C, Condition 4	Route D, Condition 1	Route A, Condition 2
3	Route C, Condition 1	Route D, Condition 2	Route A, Condition 3	Route B, Condition 4
4	Route D, Condition 3	Route A, Condition 4	Route B, Condition 1	Route C, Condition 2
5	Route A, Condition 2	Route B, Condition 3	Route C, Condition 4	Route D, Condition 1
6	Route B, Condition 4	Route C, Condition 1	Route D, Condition 2	Route A, Condition 3
7	Route C, Condition 2	Route D, Condition 3	Route A, Condition 4	Route B, Condition 1
8	Route D, Condition 4	Route A, Condition 1	Route B, Condition 2	Route C, Condition 3

This Latin square design systematically varies the presentation order of the Cognitive Distraction condition across four patterns (e.g., NNYY, YYNN, NYYN, YNNY). However, it is a recognized limitation that the Level of Map Guidance Detail condition was presented in a strictly alternating sequence for all participants (RLRL or LRLR). While this ensures that lane-level and road-level displays appear equally often in early and late trials, it does not control for potential order effects that could arise from this specific alternating pattern (e.g., RRLL was not tested). This trade-off was accepted to prioritize the robust counterbalancing of route-condition pairings within the logistical constraints of the study.

After each drive, participants completed the NASA-TLX and UEQ questionnaires and were asked to recall any errors they made and explain the reasons for them. After all the driving sessions, participants are prompted to talk about their experience on the two different navigation displays and the general driving simulation.

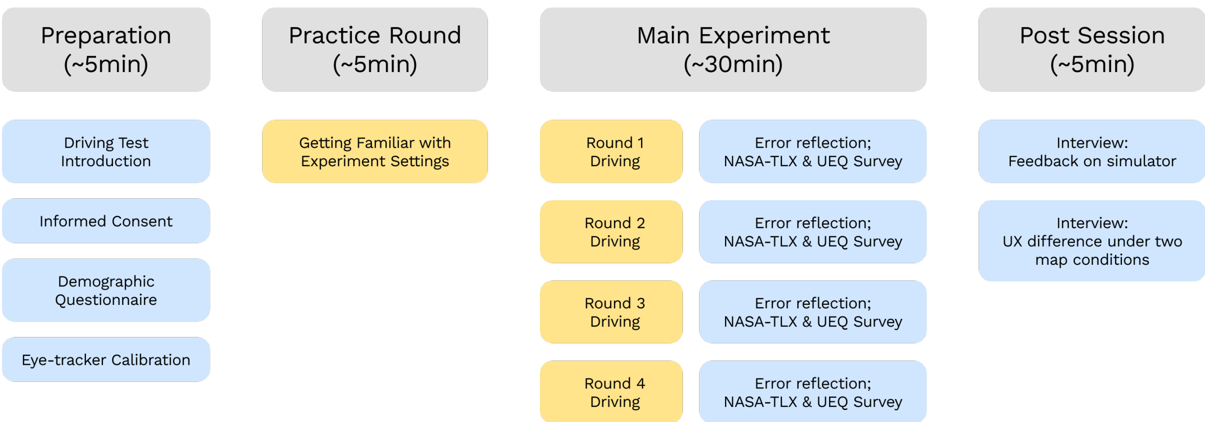


Fig. 10 Workflow of the experiment

5.7 Data Processing

Multiple data streams were recorded and synchronized for comprehensive post-session analysis. The Unity-based simulation logged driving behavior data and N-back task performance to local files. The Pupil Labs Neon eye-tracker simultaneously recorded gaze data and a video of the participant's field of view. Screen recordings of both the road view and navigation view were also captured as a backup and for qualitative review. Finally, subjective data from the NASA-TLX, UEQ, and post-drive interviews were collected manually by the researcher. This serves as the basis of following data processing work.

5.7.1 Labelling of Navigation Errors

Across all 160 sessions, 64 navigation errors were identified and labelled based on driving behavior as follows:

> **16 Missed Turns:** The driver drove past the intersection without any attempt to make a turn.
>
> **32 Wrong Turns:** The driver made a turn at an incorrect location, either before or after the correct intersection. This category also includes instances where a driver turned into the wrong way on a divided road, as the study focuses on navigational awareness over driving violations.
>
> **16 Risky Turns:** The driver nearly missed a turn or made a wrong one but corrected it with a late and abrupt maneuver that was considered risky.

Additionally, two risky turn errors were excluded due to a system bug that caused the map to rotate when the driver fixated on it, thereby introducing technical artifacts unrelated to the cognitive processes being examined.

5.7.2 Labelling of Cognitive Failures

The 64 navigation errors were manually coded with cognitive failures, supported by post-drive interviews, driving behavior and gaze data, based on the following guidelines:

> **Perception Failure:** The driver failed to notice the upcoming turn, or to gather sufficient visual information from the navigation display before making an error. This was identified by a critically low number of fixations (typically 0-2 fixations, while 3.77 on average for correct turns) and low fixation durations (74.39ms for perception failures on average, 127.04ms for correct turns).
>
> **Interpretation Failure:** The driver was aware of the turn but misunderstood the navigation cues or failed to match the map to reality. This was identified in cases where a sufficient number of fixations were made on the navigation screen (4.29 fixations on average), indicating the driver was aware of the upcoming turn, yet still performed an incorrect maneuver.

Decision-Making Failure: The driver correctly perceived and interpreted the instruction too late and then misjudged the risk of correcting the potential error, resulting in an unsafe maneuver.

In certain instances, distinguishing between perception failure and interpretation failure was challenging, particularly under missed turns and wrong turns. For example, consider a case where a driver made a wrong turn after a single fixation on the navigation screen 100 meters before the intersection. This behavior suggests a combination of perception failure (insufficient fixation failed to gather enough information) and interpretation failure (misprocessing the limited information available), which collectively resulted in the navigation error. In cases like this, both perception failure and interpretation failure are labelled. In addition, all risky turns were primarily caused by perception or interpretation failures during the initial cognitive process, followed by decision-making failures during the risky maneuver.

5.7.3 Main Effect Analyses

The analysis of navigation error rates and subjective measures utilized the complete dataset of 160 sessions (40 participants × 4 conditions). However, for the continuous analysis of driving behavior and eye-tracking metrics, a data quality screening was performed. Due to technical issues such as logging failures or poor eye-tracker calibration, this resulted in the exclusion of some sessions. Consequently, the driving behavior analysis was conducted on 151 sessions, and the eye-tracking analysis was based on 145 sessions. Furthermore, to ensure these continuous analyses were not biased by the abnormal behaviors surrounding navigation errors, time windows corresponding to these error events (spanning from 80m before to 40m after the intersection) were excluded from the driving and gaze datasets.

Different statistical models were selected to analyze the main effects of cognitive distraction and level of map guidance detail on different dependent variables, tailoring to the specific statistical properties of each dataset.

1. **Navigation Error Rate**: These variables are count-based with extreme zero-inflation (65–99%) and sparse, non-parametric distributions. To reduce bias and avoid assumptions of normality, we collapsed the data into two conditions ("Distraction vs. No Distraction" and "LLN vs. No LLN") and applied Wilcoxon signed-rank tests for paired comparisons *(Wilcoxon, 1945)*. This non-parametric approach is robust against non-normality and zero-inflation. A limitation is that collapsing data reduces granularity and mask interaction effects.
2. **Subjective Measures** (NASA-TLX, UEQ): These scales are ordinal in nature. When data violated normality assumptions, we used Aligned Rank Transform (ART) ANOVA to retain factorial interpretability while respecting the ordinal scale *(Wobbrock et al., 2011)*. When normality was satisfied, we applied repeated measures ANOVA (RM-ANOVA), which provides familiar effect size estimates and straightforward interpretability *(Scott E. Maxwell et al., 2018)*.
3. **Eye-Tracking Data**: These are continuous variables subject to strong inter-individual variability and occasional missing data. To address this, we used linear mixed-effects

models (LMM) when normality assumptions were met *(Pinheiro & Bates, 2000)*, and generalized linear mixed models (GLMM) when they were not *(Andrew Gelman & Jennifer Hill, 2007)*. Mixed models allow the inclusion of random effects, improving generalizability and reducing bias from individual differences.

4. **Driving Behavior Data**: These continuous outcomes also varied considerably across individuals, with some variables showing normality and others not. Following the same rationale as with eye-tracking data, LMMs and GLMMs were utilized accordingly.

6. Results

6.1 Classification of Navigation Errors and Cognitive Failures (RQ1)

The 64 identified errors were linked to 85 instances of cognitive failure. Interpretation failures were the most frequent (55 cases), followed by decision-making failure (16 cases) and perception failure (14 cases). Specifically, interpretation failures were the primary cause of wrong turns, while both perception and interpretation failures contributed equally to missed turns. Risky turns were directly linked to decision-making failures, although interpretation failures also played a major role in their occurrence.

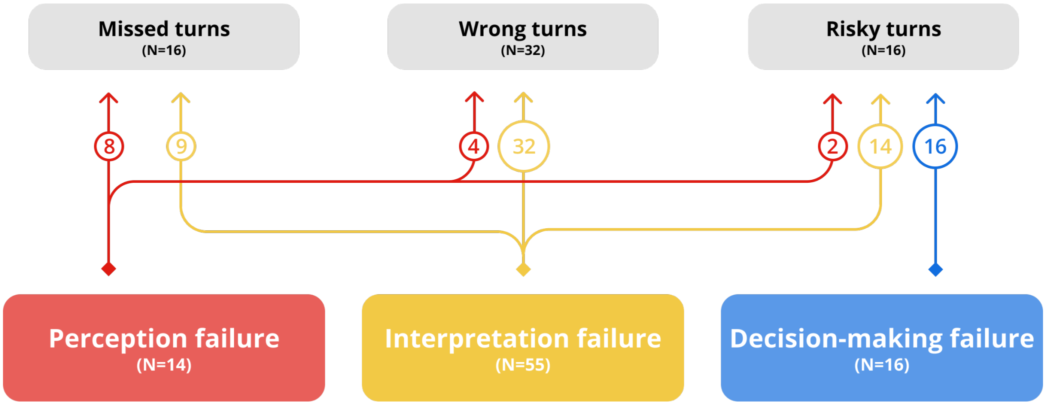


Fig. 11 Map of Cognitive Failures and Navigation Errors

Specifically, missed turn errors were attributed to both **perception failure (8 cases)** and **interpretation failure (9 cases)**.

> **Perception Failure Example**: The driver did not pay attention to the map, as evidenced by an absence of fixations on the navigation screen and no sign of decelerating until it was too late.

> **Interpretation Failure Example**: The driver was aware of the upcoming turn (indicated by multiple fixations on the navigation screen starting 100 meters before the intersection) but was distracted and failed to make the turn at the correct time. In two special cases, when lane-level navigation (LLN) was present, the driver misinterpreted the distance displayed on the map, believing the turn had not yet arrived.

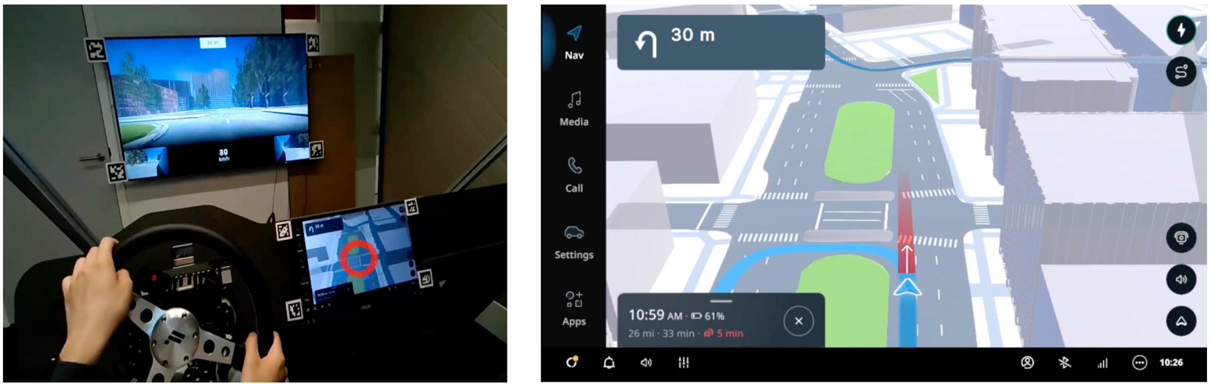


Fig. 12 Late fixations on map (30m before intersection) led to a missed turn

Wrong turn errors were primarily caused by **interpretation failure (32 cases)**, though **perception failure (4 cases)** was also identified in specific cases.

Interpretation Failure Example: At a challenging intersection where two right-turn paths were presented, a participant took the wrong path by mismatching the map with reality. As the participant explained, "I thought it was a more curved turn when I looked at the map, but when I looked at the road, I wasn't very sure."

Perception Failure Example: Another participant claimed to have failed to notice the presence of two paths altogether, stating, "I didn't notice another path on the map."

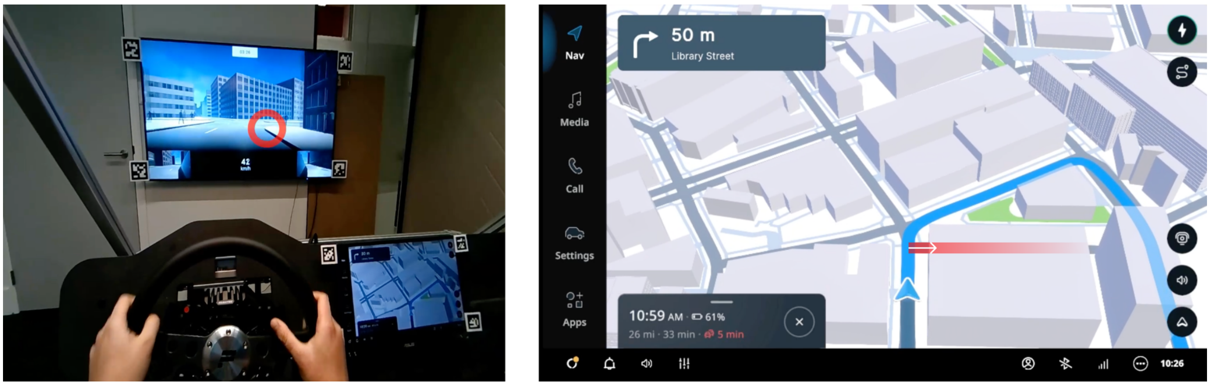


Fig. 13 Misinterpretation (fixation on the wrong path) led to a wrong turn

Risky turn errors can be understood in **two stages**:

Stage 1: Perception failure (2 cases) or interpretation failure (14 cases) led to potential navigation errors, following patterns observed in missed turns and wrong turns.

Stage 2: The driver correctly perceived and understood the navigation instruction at the last moment and attempted to correct their earlier errors. At this point, the driver may have already entered the intersection (potential missed turn) or steered into the wrong direction (potential wrong turn), requiring abrupt braking or steering adjustments. This behavior reflects **decision-making failure (16 cases)** during risky maneuvers.

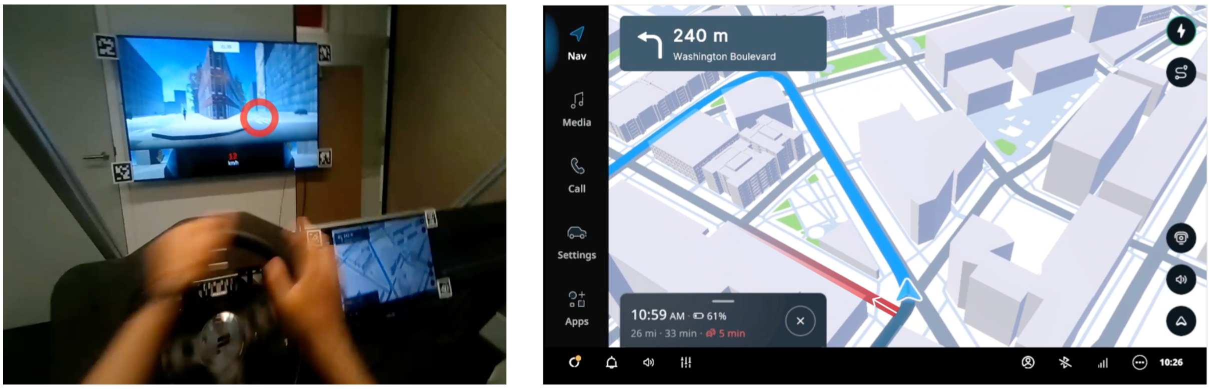


Fig. 14 Abrupt steering behavior at the middle of intersection

Having established this classification framework for navigation errors and their underlying cognitive failures, the following sections address the second research question (RQ2) by examining how these outcomes are influenced by the experimental conditions.

6.2 The Effect of Cognitive Distraction (H1)

The first hypothesis (H1) predicted that cognitive distraction would increase perception failures and missed turns. This hypothesis was not supported by the error data. However, the distraction task robustly increased cognitive load, as evidenced by subjective, behavioral, and gaze metrics.

Navigation Errors and Cognitive Failures: The Wilcoxon signed-rank test showed no significant effect of the 2-back task distraction on the rate of perception failures ($Z = 0.0$, $p = 1.0$) or missed turns ($Z = -0.420$, $p = 0.675$). Similarly, no significant effects were found for other error types or cognitive failures.

*Table 2 Distraction effects on navigation error and cognitive failure rates (Wilcoxon signed-rank test, n = 40 participants) Effect size r = Z/ √N. Significance: * p < .05, ** p < .01, *** p < .001 Direction (Increased/Decreased) is inferred from the descriptive statistics (median/mean)*

Dependent Variable	Z	p-value	Sig.	r	Effect Size	Direction
Missed Turns	-0.420	.675		-.066	negligible	Decreased
Wrong Turns	-0.410	.682		-.065	negligible	Increased
Risky Turns	-0.054	.957		-.009	negligible	~No change
Perception Failures	0.000	1.000		.000	negligible	~No change
Interpretation Failures	-0.173	.862		-.027	negligible	Decreased

Decision-Making Failures	-0.054	.957		-.009	negligible	~No change
Total Errors	-0.102	.919		-.016	negligible	~No change

Subjective Workload: In sharp contrast, distraction had a powerful effect on subjective workload. A repeated measures ANOVA on the overall NASA-TLX score (calculated as the average of all its sub-measures) showed a strong main effect of distraction ($F(1, 38) = 91.55$, $p < .001$, ges = 0.58). This was confirmed by strong significant effects on all the subscales, tested by parametric ART ANOVA.

Table 3 Effects of Distraction and LLN on NASA-TLX overall score (repeated-measures ANOVA, n = 39 participants). Results shown as F, df, p-value, and effect size (ges). Direction is inferred from descriptive means

Dependent Variable	Predictors	F	Df	p-value	Sig.	Effect Size (ges)	Direction
NASA TLX Overall Score	Distraction	91.55	1	1.15e-11	***	0.579	Increased
	LLN	0.19	1	0.663		0.0050	Increased
	Distraction × LLN	1.79	1	0.188		0.0451	Decreased

Table 4 Distraction effects on NASA-TLX subscales (aligned rank transform ANOVA, n = 39 participants). Results shown as F, df, p-value, and effect size (rank-biserial). Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (r)	Direction
Mental Demand	184.57	1, 114	< 2e-16	***	0.740	Increased
Physical Demand	32.00	1, 114	1.163e-07	***	0.323	Increased
Temporal Demand	75.61	1, 114	2.969e-14	***	0.582	Increased
Performance	70.97	1, 114	1.242e-13	***	0.528	Decreased
Effort	88.54	1, 114	6.613e-16	***	0.603	Increased
Frustration	92.01	1, 114	2.481e-16	***	0.553	Increased

Driving Behavior: Drivers under 2-back tasks showed decreased throttle input (from 0.118 to 0.115; $\chi^2(1) = 5.12$, $p = 0.024$), throttle variability (from 0.099 to 0.093; $\chi^2(1) = 6.07$, $p = 0.014$) and acceleration variability (from 3.69 to 3.38; $\chi^2(1) = 6.85$, $p = 0.009$), indicating more conservative driving under cognitive load. Speed variability also showed a marginal decrease (from 11.48 to 10.95 km/h; $\chi^2(1) = 2.85$, $p = 0.091$).

Table 5 Distraction effects on driving behavior metrics (GLMM/LMM, n = 40 participants, 151 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI
Acceleration variability (m/s^2)	6.85	1	0.009	**	-0.22	[-0.38, -0.06]
Throttle variability	6.07	1	0.014	*	-0.07	[-0.13, -0.02]
Mean throttle input	5.12	1	0.024	*	-0.04	[-0.08, -0.01]
Speed variability (km/h)	2.85	1	0.091	.	-0.54	[-1.17, 0.09]

Gaze Behavior: Gaze patterns also changed significantly, showing several typical patterns of increased cognitive load: increased pupil diameter (from 3.90 to 4.01mm; $\chi^2(1) = 42.19$, $p < .001$) , longer saccade duration (from 73.79 to 89.81ms; $\chi^2(1) = 68.507$, $p < .001$), and more concentrated fixations on both road and navigation screens that is indicated by decreased fixation position variance on navigation screen. In this study, fixation position variance is the mean of x and y coordinate variances across all fixations within an AOI, indicating how scattered or focused the gaze pattern is.

Counter to the typical gaze-centering effect of cognitive load, distraction also led to an overall increase in saccade amplitude (from 11.5° to 13.3°; χ^2 (1) = 63.08, $p < .001$) and velocity (from 2565 to 2833 pixel/s; χ^2 (1) = 73.71, $p < .001$) across all recorded eye movements. This likely reflects the additional visual demands of the n-back task, which required participants to glance towards the steering wheel buttons for the n-back task (see Section 6.6.1).

Distraction significantly decreased fixation rates on road (from 1.38 to 1.21 fixations/sec; χ^2 (1) = 47.28, $p < .001$) and time spent fixating on road (from 62.40% to 56.64%; χ^2 (1) = 25.10, $p < .001$), suggesting visual attention shifted away from primary driving task. Total number of glance count on navigation screen showed a marginally significant increase (from 45.62 to 47.73; χ^2 (1) = 3.91, p = 0.048), indicating more frequent visual scan needed under distraction.

Table 6 Distraction effects on eye-tracking metrics (GLMM/LMM, n = 37 participants, 145 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Metrics	Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI
Navigation Screen AOI Metrics	**Navigation fixation position variance**	5.93	1	0.015	*	-0.16	[-0.29, -0.03]
	Navigation glance count	3.91	1	0.048	*	4.21	[0.04, 8.38]
	Navigation gaze position variance	3.61	1	0.058	.	-0.1	[-0.21, 0.00]
Road Screen AOI Metrics	**Time fixating on road (%)**	25.10	1	< .001	***	-6.77	[-9.47, -4.08]
	Road fixations count percent (%) [1]	55.42	1	< .001	***	-8.98	[-11.34, -6.61]

	Road gaze count percent (%) [2]	33.28	1	< .001	***	-7.45	[-9.98, -4.92]
	Road fixation rate (fixations/s)	47.28	1	< .001	***	-0.15	[-0.19, -0.11]
	Road gaze rate (gaze points/s)	24.73	1	< .001	***	-13.71	[-19.11, -8.31]
	Road fixation position variance	31.97	1	< .001	***	-0.003	[-0.004, -0.002]
	Road gaze position variance	32.66	1	< .001	***	-0.003	[-0.004, -0.002]
Other Metrics	Glance ratio road vs nav [1]	5.54	1	0.019	*	-0.22	[-0.40, -0.04]
	Avg pupil diameter (mm)	42.19	1	< .001	***	0.11	[0.08, 0.15]
	Pupil diameter variability (SD, mm)	93.34	1	< .001	***	0.07	[0.05, 0.08]
	Blink rate (blinks/s)	67.32	1	< .001	***	0.40	[0.31, 0.50]
	Avg saccade duration (ms)	63.08	1	< .001	***	2.34	[1.76, 2.91]
	Avg saccade velocity (pixels/s) [2]	73.71	1	< .001	***	315.65	[243.59, 387.72]
	Avg saccade amplitude (°) [1]	6.66	1	0.01	**	-1.08	[-1.90, -0.26]

[1]This main effect is qualified by a significant interaction effect (p < .05) detailed in Section 6.4
[2]This main effect is qualified by a marginal interaction effect (.05 < p < .10) detailed in Section 6.4

6.3 The Effect of Level of Map Guidance Detail (H2 & H3)

The second and third hypotheses predicted that lane-level navigation (LLN) would reduce interpretation and decision-making failures, thereby reducing wrong turns (H2) and risky turns (H3). The data provided strong support for H2, trending yet not significant evidence for H3. Generally, LLN showed some positive effects on vehicle control and user experiences, yet its effects on gaze behavior is more complex.

Navigation Errors and Cognitive Failures: The Wilcoxon signed-rank test revealed that LLN significantly reduced interpretation failures (from 3.8% to 2.0% of turns; Z = -2.317, p = 0.021) and consistently the frequency of wrong turns (from 2.2% to 1.1% of turns; Z = -2.132, p = 0.033). Overall, the total number of navigation errors was significantly lower in the LLN condition, decreasing from 4.2% (40 total errors) to 2.5% (24 total errors) of turns (Z = -2.049, p = 0.040). The predicted reduction in decision-making failures and risky turns (H3) was not statistically significant, though a trend was observable (p = 0.085).

Table 7 Lane-level navigation (LLN) effects on navigation error and cognitive failure rates (Wilcoxon signed-rank test, n = 40 participants). Direction (Increased/Decreased) is inferred from the descriptive statistics (median/mean)

Dependent Variable	Z	p-value	Sig.	r	Effect Size	Direction

Missed Turns	-0.632	.527		-.100	small	Increased
Wrong Turns	-2.132	.033	*	-.337	medium	Decreased
Risky Turns	-1.721	.085		-.272	small	Decreased
Perception Failures	-0.540	.589	.	-.085	negligible	Decreased
Interpretation Failures	-2.317	.021	*	-.366	medium	Decreased
Decision-Making Failures	-1.721	.085	.	-.272	small	Decreased
Total Errors	-2.049	.040	*	-.324	medium	Decreased

User Experience: The ART ANOVA showed that users subjectively preferred LLN, rating it as more Supportive, Exciting, Interesting, Inventive, and Leading Edge, which led to significantly higher overall Attractiveness ($p = 0.010$) calculated as the average of all UEQ sub-measures and Hedonic quality ($p < .001$) calculated as the average of the dimensions exciting, interesting, inventive, and leading-edge.

Table 8 LLN effects on User Experience Questionnaire (UEQ) metrics (aligned rank transform ANOVA, n = 40 participants). Results shown as F, df, p-value, and effect size (η^2). Bold entries highlight significant LLN effects. Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (η^2)	Direction
Supportive	4.48	1, 117	0.036	*	0.0369	Increased
Easy	0.55	1, 117	0.462		0.0046	Increased
Efficient	1.70	1, 117	0.195		0.0143	Increased
Clear	2.26	1, 117	0.135		0.0190	Increased
Exciting	26.77	1, 117	9.588e-07	***	0.1862	Increased
Interesting	12.92	1, 117	0.000478	***	0.0994	Increased
Inventive	27.88	1, 117	6.032e-07	***	0.1924	Increased
Leading Edge	11.04	1, 117	0.001188	**	0.0863	Increased
UEQ Attractiveness	6.94	1, 117	0.009594	**	0.0560	Increased
UEQ Pragmatic	3.18	1, 117	0.077	.	0.0264	Increased
UEQ Hedonic	27.48	1, 117	7.135e-07	***	0.1902	Increased

Driving Behavior: The only significant effect of LLN on driving performance was a reduction in the duration of driving in the wrong way designated for oncoming traffic (from

3.20s to 3.02s for non-zero trials; χ^2 (1) = 4.84, p = 0.028), indicating better situational awareness.

Table 9 LLN effects on driving behavior metrics (GLMM/LMM, n = 40 participants, 151 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI
Wrong way driving duration (s)	4.84	1	0.028	*	-0.635	[-1.20, -0.07]

Gaze Behavior: The main effect of LLN was a clear re-allocation of visual attention from the road to the navigation display. The most robust finding was a significant decrease in the time fixating on the road (from 60.48 to 58.67%; χ^2 (1) = 4.81, p = 0.028). This is further evidenced by increased gaze rate (from 9.84 to 12.38 gaze points/s; χ^2 (1) = 19.26, p < .001) on navigation screen and decreased gaze rate on road (from 125.36 to 121.22 gaze points/s; χ^2 (1) = 6.01, p = 0.014). These findings suggest a trade-off where the detailed LLN display consistently drew more visual attention at the expense of road monitoring.

Total number of glances on the navigation screen increased significantly (from 44.55 to 48.79 glances; χ^2 (1) = 9.31, p = 0.002), and the average duration of each glance also increased (from 306.58 to 338.22 ms; χ^2 (1) = 8.49, p = 0.004). In this study, glance duration is defined as the time from when the gaze shifts toward an area of interest (AOI) until it moves away. Such pattern indicates that drivers not only checked the navigation display more frequently but also spent longer processing information during each glance.

In addition, significant increases in navigation fixation position variance (from 0.009 to 0.011; χ^2 (1) = 8.94, p = 0.003) and gaze position variance (from 0.011 to 0.013; χ^2 (1) = 15.86, p < 0.001) suggest more dispersed visual scanning patterns on the navigation screen. These indicates that drivers may need to scan a wider area of the navigation interface to locate relevant information.

LLN also had a significant main effect on saccade metrics, increasing both the average saccade amplitude (from 12.26° to 12.52°; χ^2 (1) = 8.18, p = 0.004) and velocity (from 2680 to 2712 pixels/s; χ^2 (1) = 4.75, p = 0.029). However, both main effects were qualified by significant or marginal interactions with distraction.

Table 10 LLN effects on eye-tracking metrics (GLMM/LMM, n = 37 participants, 145 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Metrics	Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI
Navigation Screen AOI Metrics	Navigation percent time fixating (%) [2]	24.75	1	< .001	***	0.38	[0.23, 0.53]
	Navigation glance count	9.31	1	0.002	**	6.43	[2.30, 10.57]
	Navigation avg glance duration (ms)	8.49	1	0.004	**	0.14	[0.04, 0.23]

	Navigation avg fixation duration (ms)	8.47	1	0.004	**	0.1	[0.03, 0.18]
	Navigation fixation rate (fixations/s) [2]	22.04	1	< .001	***	0.08	[0.04, 0.11]
	Navigation gaze rate (gaze points/s)	19.26	1	< .001	***	0.31	[0.17, 0.45]
	Navigation fixations count percent (%) [2]	22.73	1	< .001	***	3.45	[2.03, 4.87]
	Navigation gaze count percent (%)	19.23	1	< .001	***	0.3	[0.16, 0.43]
	Navigation fixation position variance	8.94	1	0.003	**	0.19	[0.07, 0.32]
	Navigation gaze position variance	15.86	1	< .001	***	0.21	[0.11, 0.31]
Road Screen AOI Metrics	**Road percent time fixating (%)**	4.81	1	0.028	*	-2.94	[-5.57, -0.31]
	Road fixation rate (fixations/s)	4.97	1	0.026	*	-0.05	[-0.09, -0.01]
	Road gaze rate (gaze points/s)	6.01	1	0.014	*	-6.7	[-12.06, -1.34]
	Road fixations count percent (%) [1]	19.64	1	< .001	***	-5.3	[-7.64, -2.95]
	Road gaze count percent (%) [2]	10.62	1	0.001	**	-4.17	[-6.68, -1.66]
Other Metrics	Glance ratio road vs nav [1]	23.74	1	< .001	***	-0.45	[-0.63, -0.27]
	Avg saccade amplitude (°) [1]	8.18	1	0.004	**	0.83	[0.26, 1.41]
	Avg saccade velocity (pixels/s) [2]	4.75	1	0.029	*	79.39	[7.97, 150.81]

[1]*This main effect is qualified by a significant interaction effect (p < .05) detailed in Section 6.4*
[2]*This main effect is qualified by a marginal interaction effect (.05 < p < .10) detailed in Section 6.4*

6.4 Interaction Effects (H4)

The fourth hypothesis (H4) predicted that LLN would mitigate the negative effects of distraction. No such mitigating interaction was found on navigation errors. Instead, the interaction effects observed in gaze and driving behavior suggest that the detailed LLN display changed how cognitive distraction affected performance.

Navigation Errors and Cognitive Failures: A GLMM model test showed no significant interaction effects between cognitive distraction and level of map guidance detail in the error data.

Driving Behavior: A significant interaction effect was found for wrong way duration ($\chi^2(1) = 6.09$, $p = 0.014$), where LLN's effect on navigation errors reversed under distraction: LLN reduced wrong way duration without distraction (from 3.68s to 1.95s, non-zero trials) but increased it with distraction (from 2.81s to 3.86s, non-zero trials). Additionally, there was a marginally significant interaction effects for sudden steering changes ($\chi^2(1) = 3.38$, $p = 0.066$). While LLN was associated with fewer sudden steering inputs without distraction (175.1 without LLN, 173.1 with LLN), this benefit was reversed under cognitive load with much stronger effect (176.6 without LLN, 184.0 with LLN).

Table 11 LLN × Distraction interaction effects on driving behavior metrics (GLMM/LMM, n = 40 participants, 151 observations). Results shown as interaction coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI	Direction
Wrong way driving duration (s)	6.09	1	0.014	*	0.96	[0.20, 1.71]	Distraction reverses LLN's effect, from decreasing to increasing duration
Sudden steering changes (count)	3.38	1	0.066	.	0.05	[-0.00, 0.11]	Distraction reverses LLN's effect, from decreasing to increasing changes

Gaze Behavior: Several significant effects and trends toward significance were observed, indicating that distraction and mutually impede each other's impact on gaze behaviors. For example, LLN significantly reversed amplitude increase under distraction (from +0.8 to -0.2; χ^2 (1) = 6. 66, p = 0.010) and mitigates the reduction in fixation counts on the road (from -5.3 to -1.1; χ^2 (1) = 6. 01, p = 0.014) under distraction. Conversely, distraction significantly reduces LLN's effect on glance ratio (from -0.45 to -0.14; χ^2 (1) = 5. 42, p = 0.020). This is further supported by distraction's marginally significant effect on attenuating the increase in fixation rate, percentage of fixation count, and time spent fixating on navigation screen, all of which are significantly influenced by LLN. These findings suggest that the increased attention to navigation associated with LLN may be diminished under cognitive load, while the decreased attention to road resulting from distraction can be mitigated by LLN.

Table 12 LLN × Distraction interaction effects on eye-tracking metrics (GLMM/LMM, n = 37 participants, 145 observations). Results shown as interaction coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI	Direction
Avg saccade amplitude (°)	6.66	1	0.010	**	-1.08	[-1.90, -0.26]	LLN reverses amplitude increase under distraction
Avg saccade velocity (pixels/s)	3.22	1	0.073	.	-93.7	[-196.10, 8.70]	LLN reverses velocity increase under distraction
Glance ratio road vs nav	5.42	1	0.020	*	0.31	[0.05, 0.57]	Distraction reduces LLN's effect on glance ratio
Road fixations count percent (%)	6.01	1	0.014	*	4.2	[0.84, 7.56]	LLN mitigates distraction's effect on road fixation count
Road gaze count percent (%)	3.08	1	0.079	.	3.22	[-0.38, 6.81]	LLN mitigates distraction's effect on road gaze count
Navigation percent time fixating (%)	3.79	1	0.051	.	-0.21	[-0.43, 0.00]	Distraction reduces LLN's effect on percent time fixating
Navigation fixation rate (fixations/s)	3.48	1	0.062	.	-0.04	[-0.09, 0.00]	Distraction reduces LLN's effect on fixation rate
Navigation fixations count percent (%)	3.37	1	0.066	.	-1.9	[-3.94, 0.13]	Distraction reduces LLN's effect on fixation count

6.5 Driving Experience as Factor

For exploratory analysis, the sample was divided into two groups based on self-reported driving frequency: "Less experienced" (drive less than once a week, N=17) and "More experienced" (drive at least once a week, N=23).

6.5.1 Subgroup Analysis: Experience-Dependent Effects of LLN and Distraction

To further investigate the role of driving experience and address potential effect masking in the combined analysis, we conducted subgroup analyses by running separate statistical models for "Less experienced" and "More experienced" driver groups using the same statistical models as combined analysis.

Navigation Errors and Cognitive Failures: The benefits of LLN were almost exclusively observed in the More Experience group. They showed a significant reduction in Interpretation Failures (from 4.2% to 1.3%; Z = -2.724, p = 0.006), Wrong Turns (from 2.4% to 0.5%; Z = -2.673, p = 0.008), and Total Errors (from 4.9% to 1.8%; Z = -2.686, p = 0.007) when using LLN. No significant beneficial effect was found for the Less Experience group. However, a negative trend was found in the Less Experienced group, where LLN was associated with an increase in Missed Turns (from 0.2% to 1.2% of turns; Z= -2.000, p=0.046).

Table 13 LLN effects on navigation error and cognitive failure rates in the more experienced group (Wilcoxon signed-rank test, n = 23 participants). Direction (Increased/Decreased) is inferred from the descriptive statistics (median/mean)

Dependent Variable	Z	p-value	Sig.	r	Effect Size	Direction
Missed Turns	-0.816	.414		-.170	small	Decreased
Wrong Turns	-2.673	.008	**	-.557	large	Decreased
Risky Turns	-1.179	.238		-.246	small	Decreased
Perception Failures	-1.406	.160		-.293	small	Decreased
Interpretation Failures	-2.724	.006	**	-.568	large	Decreased
Decision-Making Failures	-1.179	.238		-.246	small	Decreased
Total Errors	-2.686	.007	**	-.560	large	Decreased

Table 14 LLN effects on navigation error and cognitive failure rates in the less experienced group (Wilcoxon signed-rank test, n = 17 participants). Direction (Increased/Decreased) is inferred from the descriptive statistics (median/mean)

Dependent Variable	Z	p-value	Sig.	r	Effect Size	Direction
Missed Turns	-2.000	.046	*	-.485	medium	Increased
Wrong Turns	0.000	1.000		.000	negligible	~No change

Risky Turns	-1.342	.180		-.325	medium	Decreased
Perception Failures	-1.732	.083	.	-.420	medium	Increased
Interpretation Failures	-0.263	.793		-.064	negligible	Decreased
Decision-Making Failures	-1.342	.180		-.325	medium	Decreased
Total Errors	-0.258	.796		-.063	negligible	Increased

User Experience: Subgroup analysis showed LLN's consistent effect on hedonic measures (Inventive, Exciting). Additionally, LLN's effect on pragmatic measures (calculated as the average of the dimensions supportive, easy, efficient, and clear) were found exclusively for more experienced drivers, who reported it as supportive (F=5.23, p=0.025) and clear (F=4.46, p=0.038).

Subjective Workload: Subgroup analysis showed LLN reduced the effort needed in tasks (F=4.74, p=0.033) and overall subjective workload (from 9.49 to 9.06, F=, 4.06, p=0.056) for More Experience group In contrast, there's a significant effect found in increasing the overall subjective workload for Less Experience group (from 8.79 to 9.62, F=5.94, p=0.028).

Table 15 LLN effects on UEQ metrics and NASA-TLX Effort score in the more experienced group (aligned rank transform ANOVA, n = 23 participants). Results shown as F, df, p-value, and effect size (rank-biserial). Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (r)	Direction
Supportive	5.23	1, 66	0.025	*	0.154	Increased
Clear	4.46	1, 66	0.038	*	0.179	Increased
Exciting	11.92	1, 66	0.001	***	0.262	Increased
Inventive	7.61	1, 66	0.008	**	0.259	Increased
UEQ Attractiveness	9.48	1, 66	0.003	**	0.249	Increased
UEQ Pragmatic	8.79	1, 66	0.004	**	0.203	Increased
Effort	4.74	1, 66	0.033	*	0.147	Decreased

Table 16 LLN effects on UEQ metric Hedonic and NASA-TLX overall score in the more experienced group (repeated-measures ANOVA, n = 23 participants). Results shown as F, df, p-value, and effect size (ges). Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (ges)	Direction
UEQ Hedonic	7.50	1, 22	0.012	*	0.0001	Increased
NASA TLX Overall Score	5.94	1, 15	0.027	*	0.048	Decreased

Table 17 LLN effects on NASA-TLX overall score in the less experienced group (aligned rank transform ANOVA, n = 17 participants). Results shown as F, df, p-value, and effect size (rank-biserial). Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (r)	Direction
Exciting	13.97	1, 48	<0.001	***	0.328	Increased
Interesting	7.84	1, 48	0.007	**	0.234	Increased
Inventive	23.28	1, 48	<0.001	***	0.373	Increased
Leading Edge	10.43	1, 48	0.002	**	0.304	Increased
UEQ Hedonic	21.52	1, 48	<0.001	***	0.372	Increased

Table 18 LLN effects on NASA-TLX metrics in the less experienced group (repeated-measures, n = 16 participants). Results shown as F, df, p-value, and effect size (η^2). Direction is inferred from descriptive means

Dependent Variable	F	Df	p-value	Sig.	Effect Size (ges)	Direction
NASA TLX Overall Score	5.94	1, 15	0.0277	*	0.195	Increased
Effort	3.67	1, 15	0.0747	.	0.053	Increased

Gaze Behavior: Both experience groups demonstrated similar patterns of attention reallocation from road to navigation display. However, for more experienced drivers, most of relevant metrics exhibited interaction effects with distraction. For example, distraction significantly reduces LLN's effect on increasing fixation count percentage (χ^2 (1) = 5.56, p = 0.018) and time spent fixating on navigation display (χ^2 (1) = 6.93, p = 0.008). This suggests that more experienced drivers have more flexibility in attention management that adapt to distracted conditions. In contrast, such strategic adaptation was not observed in less experienced drivers. Less experienced drivers showed more pronounced LLN effects on navigation attention metrics, accompanied by significantly greater reductions in road monitoring.

Furthermore, LLN significantly increased average glance duration (from 297.12 to 328.23ms; χ^2 (1) = 8.87, p = 0.003) and fixation duration (from 135.40 to 149.83ms; χ^2 (1) = 8.86, p = 0.003) exclusively in the more experienced group, indicating different information processing strategies. In addition, both groups showed significant increases in fixation and gaze position variance on the navigation screen under LLN, suggesting similar visual scanning patterns with broader search areas.

Table 19 LLN effects on eye-tracking metrics in the more experienced group (GLMM/LMM, n = 22 participants, 87 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Metrics	Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI

Navigation Screen AOI Metrics	**Navigation gaze rate (gaze points/s)**	15.27	1	< .001	***	3.99	[1.99, 6.00]
	Navigation fixation rate (fixations/s) [1]	19.56	1	< .001	***	0.1	[0.05, 0.14]
	Navigation percent time fixating (%) [1]	24.00	1	< .001	***	0.48	[0.29, 0.67]
	Navigation glance count [2]	7.22	1	0.007	**	7.68	[2.08, 13.28]
	Navigation fixations count percent (%) [1]	19.36	1	< .001	***	4.25	[2.35, 6.14]
	Navigation gaze count percent (%) [2]	15.78	1	< .001	***	0.35	[0.18, 0.52]
	Navigation avg glance duration (ms)	8.87	1	0.003	**	0.19	[0.07, 0.32]
	Navigation avg fixation duration (ms)	8.86	1	0.003	**	20.08	[6.86, 33.30]
	Navigation fixation position variance	4.03	1	0.045	*	0.17	[0.00, 0.34]
	Navigation gaze position variance	6.94	1	0.008	**	0.19	[0.05, 0.33]
Road Screen AOI Metrics	Road fixations count percent (%) [1]	10.08	1	0.002	**	-5.32	[-8.60, -2.03]
	Road gaze count percent (%)	4.05	1	0.044	*	-3.68	[-7.27, -0.10]
Other Metrics	Glance ratio road vs nav [1]	21.2	1	< .001	***	-0.53	[-0.75, -0.30]
	Avg saccade amplitude (°) [1]	5.61	1	0.018	*	0.96	[0.17, 1.75]
	Avg saccade velocity (pixels/s) [2]	3.26	1	0.071	.	93.26	[-7.96, 194.48]

[1]This main effect is qualified by a significant interaction effect (p < .05).
[2]This main effect is qualified by a marginal interaction effect (.05 < p < .10).

Table 20 LLN effects on eye-tracking metrics in the less experienced group (GLMM/LMM, n = 15 participants, 58 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Metrics	Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI
Navigation Screen AOI Metrics	**Time fixating on Navigation (%)**	3.28	1	0.07	.	0.87	[-0.07, 1.82]
	Navigation fixation rate (fixations/s)	3.77	1	0.052	.	0.05	[-0.00, 0.09]
	Navigation gaze rate (gaze points/s)	3.38	1	0.066	.	1.95	[-0.13, 4.02]
	Navigation fixations count percent (%)	4.5	1	0.034	*	0.16	[0.01, 0.31]
	Navigation gaze count percent (%)	5.02	1	0.025	*	1.2	[0.15, 2.25]
	Navigation fixation position variance	6.45	1	0.011	*	0.23	[0.05, 0.41]
	Navigation gaze position variance	11.27	1	< .001	***	0.25	[0.10, 0.40]
Road Screen	**Road percent time fixating (%)** [1]	11.27	1	< .001	***	-6.85	[-10.84, -2.85]

AOI Metrics	**Road fixation rate (fixations/s)**	5.18	1	0.023	*	-0.09	[-0.16, -0.01]
	Road gaze rate (gaze points/s) [1]	13.76	1	< .001	***	-14.62	[-22.34, -6.89]
	Road fixations count percent (%)	10.24	1	0.001	**	-0.08	[-0.13, -0.03]
	Road gaze count percent (%)	8.27	1	0.004	**	-4.89	[-8.22, -1.56]
Other Metrics	**Glance ratio road vs nav**	5.19	1	0.023	*	-0.34	[-0.63, -0.05]
	Blink rate (blinks/s)	2.93	1	0.087	.	0.04	[-0.01, 0.09]

[1]This main effect is qualified by a significant interaction effect ($p < .05$).

6.5.2 Three-Way Interaction Analysis: How Experience Influences LLN and Distraction Effects

To explore whether driver experience influenced the effectiveness of lane-level navigation, we employed the same models for each dependent variable, but with driving experience as a between-subject factor.

Subjective Measures: Both groups reported a significantly higher workload under cognitive distraction. However, their workload perception of LLN differed markedly. The More Experienced group showed decreased workload with LLN (lower temporal demand, effort, and NASA TLX overall load score), while the Less Experienced group showed increased workload with LLN (higher scores on these same measures). This suggests that detailed lane-level navigation provides cognitive benefits for experienced drivers but may be overwhelming for less experienced drivers. In contrast, both groups showed similar subjective preferences for LLN across hedonic dimensions (e.g., Exciting, Interesting, Inventive), indicating that user experience ratings were consistent regardless of experience level.

Table 21 LLN × Experience interaction effects on workload variables (aligned rank transform ANOVA, n = 39 participants). Results shown as F, df, p-value, and effect size (η^2). Direction is inferred from descriptive means, showing the opposing effect of LLN on each experience group

Dependent Variable	F	Df	p-value	Sig.	Effect Size (η^2)	Direction (Less Exp.)	Direction (More Exp.)
Temporal Demand	4.53	1, 111	0.0356	*	0.039	Increased	Decreased
Effort	8.39	1, 111	0.0046	**	0.070	Increased	Decreased
NASA TLX Overall Score	10.95	1, 37	0.0021	**	0.228	Increased	Decreased

Gaze Behavior: Although not statistically significant, driving experience, that is reflected by driving frequency, showed trends towards significance on several gaze metrics. More experienced drivers exhibited higher gaze position variance on the navigation screen (0.012 vs 0.011; χ^2 (1) = 3.19, p = 0.074), suggesting a broader visual scanning strategy. They also demonstrated shorter fixation duration (449.43 vs 514.48ms; χ^2 (1) = 3.20, p = 0.074) and spent less percentage of time fixating on road (58.67 vs 60.94%; χ^2 (1) = 2.85, p = 0.091), indicating less effort required for road monitoring.

Table 22 Experience group main effects on eye-tracking metrics (GLMM/LMM, n = 37 participants, 145 observations). Results shown as model coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI	Direction
Navigation gaze position variance	3.19	1	0.074	.	0.21	[-0.02, 0.44]	More experienced show higher variance
Road avg fixation duration (ms)	3.20	1	0.074	.	-65.41	[-137.07, 6.24]	More experienced show shorter fixations
Road percent time fixating (%) [1]	2.85	1	0.091	.	-5	[-10.81, 0.81]	More experienced show lower fixation

[1]This main effect is qualified by a significant interaction effect (p < .05).

Several significant and marginally significant three-way interactions emerged between LLN, distraction, and experience. More experienced drivers showed stronger cognitive load responses to distraction, with significantly higher pupil diameter variability (χ^2 (1) = 7.09, p = 0.008) and more concentrated fixation patterns on navigation displays (χ^2 (1) = 4.99, p = 0.025). LLN's attention-reallocating effects were consistently weaker for more experienced drivers, as evidenced by significant LLN × Experience interactions for time fixating on road (χ^2 (1) = 5.97, p = 0.015) and road gaze rate (χ^2 (1) = 5.88, p = 0.015). Under distraction, the group differences in LLN's effects on navigation attention metrics tended to shrink, as shown by marginal three-way interactions for navigation percent time fixating (χ^2 (1) = 3.28, p = 0.070) and navigation fixation rate (χ^2 (1) = 2.94, p = 0.086).

Table 23 LLN × Distraction × Experience interaction effects on eye-tracking metrics (GLMM/LMM, n = 37 participants, 145 observations). Results shown as interaction coefficients (β), χ^2, df, p-value, and 95% CI

Dependent Variable	Predictor(s)	χ^2	Df	p-value	Sig.	Estimate (β)	95% CI	Direction
Pupil diameter variability (SD, mm)	Distraction × Experience	7.09	1	0.008	**	0.04	[0.01, 0.06]	Distraction's effect is stronger for More Exp.
Navigation fixation position variance	Distraction × Experience	4.99	1	0.025	*	-0.29	[-0.54, -0.04]	Distraction's effect is stronger for More Exp.
Road gaze rate (gaze points/s)	LLN × Experience	5.88	1	0.015	*	13.31	[2.55, 24.08]	LLN's effect is weaker for More Exp.
Time fixating on road (%)	LLN × Experience	5.97	1	0.015	*	6.57	[1.30, 11.84]	LLN's effect is weaker for More Exp.
	LLN × Distraction × Experience	2.9	1	0.089	.	-6.59	[-14.18, 0.99]	With distraction, the group difference in LLN's effect shrinks
Navigation percent time fixating (%)	LLN × Distraction × Experience	3.28	1	0.07	.	-0.4	[-0.83, 0.03]	With distraction, the group difference in LLN's effect shrinks

Navigation Fixation rate (fixations/s)	LLN × Distraction × Experience	2.94	1	0.086	.	-0.08	[-0.17, 0.01]	With distraction, the group difference in LLN's effect shrinks
Navigation avg glance duration (ms)	LLN × Distraction × Experience	2.76	1	0.096	.	-0.22	[-0.49, 0.04]	With distraction, the group difference in LLN's effect shrinks
Avg saccade velocity (pixels/s)	Distraction × Experience	3.34	1	0.068	.	135.81	[-9.87, 281.48]	Distraction's effect is stronger for More Exp.
Blink rate (blinks/s)	Distraction × Experience	3.27	1	0.07	.	0.17	[-0.01, 0.36]	Distraction's effect is stronger for More Exp.

6.6 Turn- by-Turn Analysis

6.6.1 Turn-by-Turn Performance Cognitive Load Dynamics

To investigate the transient effects of cognitive load obscured by session-level aggregation, we conducted two granular, turn-by-turn analyses.

First, an event-related analysis compared n-back accuracy within standardized 50m–20m windows surrounding navigation error events versus correctly executed turns. As is shown in Fig.15, this within-subject comparison revealed that in the moments preceding a navigation error, n-back accuracy was significantly lower than before a correct turn (32.8% vs. 54.0%; $p = 0.047$, $d = 0.54$). Accuracy declined even more sharply immediately following the error (16.2% vs. 55.6%; $p = 0.003$, $d = 1.13$).

Second, a contingent performance analysis examined the relationship between momentary n-back performance and navigational success across all turns. Turns were categorized into tertiles (low, mid, high) based on each participant's relative n-back accuracy. Although not statistically significant ($p = 0.0668$), a strong trend emerged: turns where a participant's n-back accuracy was in their lowest tertile were associated with the highest navigation error rate (7.1%), compared with turns in the middle (3.9%) and highest tertiles (1.0%).

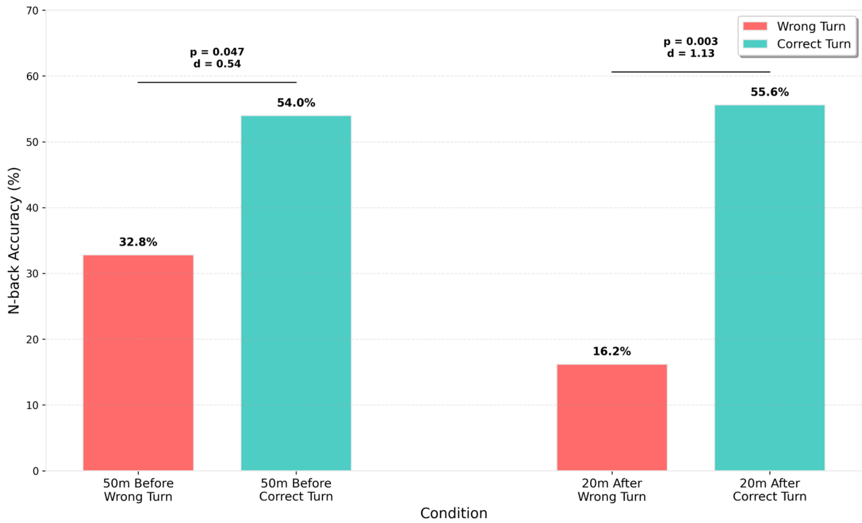


Fig. 15 N-back Accuracy by Turn Type (Correct/Errored) and Distance to the Turn (50m before/ 20m after)

Together, these exploratory findings indicate that while drivers can compensate for cognitive load overall, acute and transient periods of cognitive overload are strongly associated with navigation errors at critical moments.

6.6.2 The Role of Intersection Complexity

To further explore factors influencing navigation errors, an exploratory analysis was conducted on the role of intersection complexity. Intersections were categorized into three levels: Low (41 intersections), Mid (5 intersections), and High (2 intersections) based on error rates at the intersections: on average 1.3% at low-complexity intersections, 9.0% at mid-complexity and 31.2% at high-complexity intersections.

Lane-Level Navigation (LLN)'s effectiveness in reducing errors appeared to be moderated by complexity. The analysis of error rate reduction showed that the benefit of LLN was minimal at low-complexity intersections (-0.6 percentage points), moderate at mid-complexity (-6.0 percentage points), and most pronounced at high-complexity intersections (-12.5 percentage points). However, these differences were not statistically significant ($p > 0.05$ for all complexity levels), likely due to the limited sample size, especially the high-complexity intersections with only 80 cases. These findings, while not conclusive, strongly suggest that the benefits of detailed guidance systems like LLN are more obvious in the most challenging scenarios. This highlights a valuable direction for future research with larger datasets to statistically confirm this interaction.

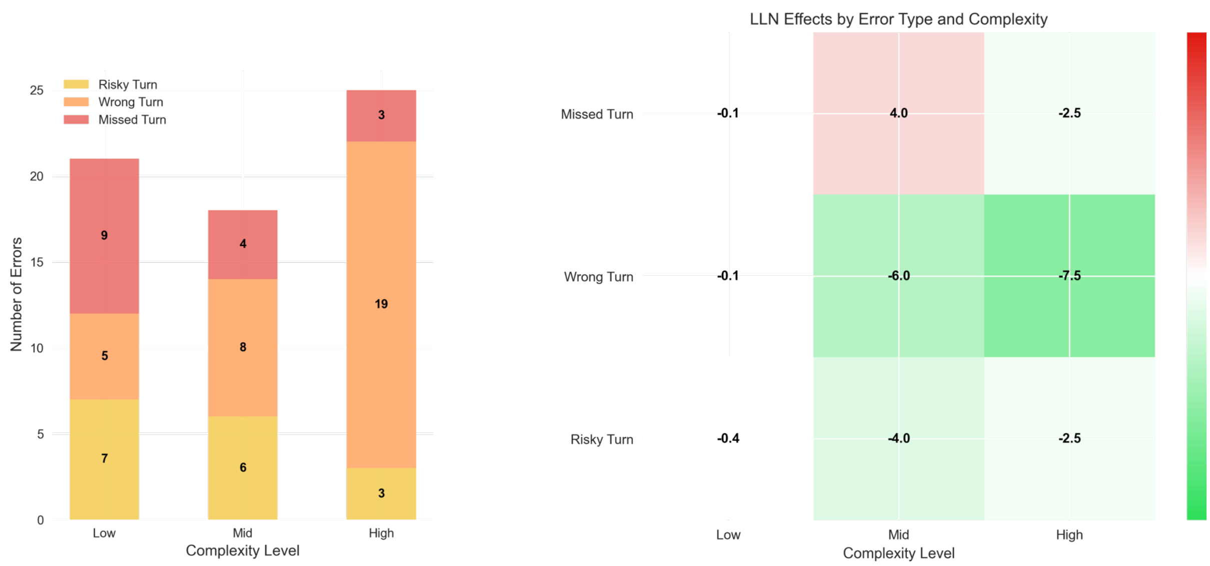


Fig. 16 Error Counts by Intersection Complexity (left), and LLN Effects on Navigation Error Rates by Error Type and Intersection Complexity (right)

7. Discussion

7.1 The Unexpectedly Low Impact of Cognitive Distraction

Contrary to H1, the auditory 2-back task did not significantly increase perception failures or missed turns across the drive, despite robust increases in subjective workload (Tables 2-4). More conservative driving behavior, such as decreased throttle input and reduced acceleration variability, suggests that participants compensated for increased cognitive demands by strategically prioritizing the primary task (Table 5).

Gaze data provides a more complex picture (Table 6). Increased pupil diameter and concentrated gaze behaviors are consistent with elevated cognitive load *(Palinko et al., 2010; Ringhand et al., 2022)*. However, saccades were observed to become larger and faster, against typical pattern under distraction *(Yuen et al., 2021)*. This pattern has also been reported by Savage et al. *(2020)*, who found faster saccade peak velocities under high secondary cognitive task demand. In our study, another likely explanation is methodological. Drivers were asked to press buttons on the steering wheel, which as well diverts their visual attention. This explains both the larger glances caused by the driver looking down at the buttons and the reduced fixation time on the navigation and road displays, suggesting impaired situational awareness.

At the turn level, however, clear cognitive load effects emerged, as detailed in our event-related analysis (Section 6.6.1). The analysis of standardized 50m–20m windows around navigation errors showed substantial drops in n-back accuracy. Before errors, accuracy was markedly reduced, indicating increased load and limited cognitive resources. Accuracy declined further after errors, consistent with drivers disengaging from the secondary task to recover and reorient. These dynamics strongly suggest that participants strategically shed the n-back task to preserve driving performance, which is a known phenomenon in distraction research *(Engström et al., 2017; Kidd et al., 2016; Öztürk et al., 2023)*.

Our contingent performance analysis (Section 6.6.1) reinforced this interpretation. Although not statistically significant ($p = 0.0668$), turns with the lowest relative n-back accuracy showed the highest error rate (7.1%) compared with middle (3.9%) and highest accuracy (1.0%). This indicates that aggregated performance measures may mask effects of cognitive load during critical navigation moments. This aligns with findings by Niezgoda et al. *(2015)*: driving metrics such as speed and steering deviations may lack sensitivity to distinguish between varying levels of cognitive workload in realistic driving scenarios.

Finally, the characteristics of our simulated environment likely moderated overall effects. As Fu et al. *(2019)* observed, distraction-related impairments become most evident in complex and demanding contexts. The simplified driving tasks used in the study lacked demanding scenarios, which may explain why error rates remained comparable to the no-distraction condition despite clear signs of cognitive load at the turn level.

7.2 LLN's Effectiveness in Reducing Navigation Errors

The central finding of this research is the significant main effect of lane-level navigation (LLN) in reducing interpretation failures and wrong turns, which contributed to an overall reduction in total navigation errors (Table 7). Interpretation failures accounted for 65% (55 out of 85) of cognitive errors, underscoring the critical role of LLN in mitigating these errors and improving navigation performance. Qualitative data indicates that participants frequently experienced confusion at complex intersections, misjudged turning distances, or struggled to connect the abstract map with the real-world scene *(Jalayer et al., 2016; Morris et al., 2024)*. By providing detailed visual instructions that highlight the exact lane for a maneuver, the LLN appears to address this core problem. The finding aligned with study of Lin et al. *(2010)* where they found sub-window on navigation display decreases navigation errors by 50% by highlighting upcoming intersection in a larger scale.

LLN also demonstrated notable effects in reducing decision-making failures and risky turns, partially supporting H3. This relationship is likely indirect, as risky turns typically arise from late corrections following a moment of confusion or interpretation difficulty (14 out of 16 cases). By improving the clarity of navigation information, LLN allows for earlier and more confident situation awareness. This gives drivers more time to prepare and execute maneuvers smoothly, reducing the likelihood of the risky, last-second actions *(Ucar et al., 2023)*. As evidence, LLN showed positive effects on driving performance by reducing wrong way driving duration (Table 9), suggesting better navigation performance without compromising vehicle control.

Gaze behaviors revealed that LLN significantly reallocates attention from road to navigation screen (Table10). Descriptive statistics showed that this change remained within an acceptable range: the proportion of time spent fixating on the road decreased from 60.48% to 58.67%, whereas fixations on the navigation screen increased from 3.88% to 5.06%. Drivers using LLN also exhibited a different information processing strategy, with more frequent longer fixations on the navigation display for information search, suggesting increased visual demand from navigation *(Yared et al., 2024)*. Importantly, increased attention to LLN was not detrimental as enhanced focus on the navigation screen provides drivers with more opportunities to understand the map and thus help reduce interpretation failures. Prior research confirms that necessary glances away from the road can enhance situational awareness *(Kircher et al., 2020)*, which in this study translated to improved navigational performance and shorter wrong-way durations. Additionally, gaze data revealed slightly more dispersed visual scanning (fixation position variance increased from 0.009 to 0.011), likely due to the closer view of the map in LLN requiring wider scanning for the same turn.

Finally, LLN significantly enhanced subjective user experience across multiple dimensions (Table 8). Participants rated LLN as more exciting, interesting, inventive, and leading-edge, resulting in higher overall attractiveness and hedonic quality.

7.3 The Interplay of Distraction and Level of Map Guidance Detail

Due to the limitations of the Wilcoxon signed-rank test, interaction effects could not be assessed. Therefore, a supplemental GLMM analysis was conducted to examine interaction effects between distraction and the level of map detail guidance. This analysis revealed no significant effects on any of the navigation error rate measures, indicating LLN's benefits on navigation performance are largely consistent regardless of distraction.

In contrast, significant interactions emerged in driving behavior and gaze data (Tables 11–12). For driving behavior, wrong-way duration showed a significant interaction, where LLN reduced duration without distraction but increased it under distraction. Similarly, sudden steering changes showed a marginal interaction, suggesting LLN's control benefits may diminish under cognitive load.

For gaze behavior, LLN mitigated distraction's negative impact on road monitoring, reflected in interaction effects on road fixation and gaze count percent. Conversely, distraction attenuated LLN's attention-reallocation toward the navigation screen. Saccade dynamics also interacted: LLN reversed the distraction-related increase in saccade amplitude and showed a marginal reduction in saccade velocity increases. Together, these results indicate that while LLN consistently improves navigation performance, its effects on vehicle control and attention allocation are context-dependent under cognitive load, mitigating some distraction costs (road monitoring) while in certain cases, reversing control benefits (wrong way duration and sudden steering).

7.4 LLN's Effect on Different Experience Groups

Subgroup analyses consistently showed that more experienced drivers benefited most from LLN. For this group, LLN reduced wrong turns, interpretation failures, and total navigation errors (Tables 13), while it had no significant positive effect for less experienced drivers. In contrast, LLN tended to increase missed turns and perception failures among less experienced drivers (Table 14). This difference is reflected in subjective measures. Less experienced drivers reported higher overall workload and greater effort when using LLN (Table 18), while more experienced drivers experienced reduced workload (Table 16) and found LLN significantly clearer and more supportive in addition to hedonic benefits (Table 15).

Gaze behavior further clarified these effects. Both experience groups shifted attention from the road to the navigation screen, but differences emerged in cognitive flexibility. For more experienced drivers, attentional metrics showed an interaction between distraction and LLN (Table 19): under distraction, the LLN-induced increase in attention to the navigation screen was reduced. This indicates their strategic adaptation to engage with LLN when undistracted and to reallocate cognitive resources when needed. Less experienced drivers, however, showed more rigid attentional allocation, with reduced road monitoring under LLN (Table 20), suggesting that LLN may impose excessive cognitive demands for them. Baseline data confirmed this: less experienced drivers spent 3.9% more time fixating on the road and were more affected by LLN-induced attention shifts (2.3× larger reduction in road fixation) than more experienced drivers.

For more experienced drivers, LLN increased glance duration on the navigation screen, suggesting adoption of a different information processing strategy with deeper engagement in visual information. Less experienced drivers did not adopt this strategy. LLN also increased fixation position variance on the navigation screen for both groups, reflecting broader visual scanning, and this effect was more pronounced in less experienced drivers. However, at baseline, more experienced drivers naturally exhibited broader gaze patterns than less experienced drivers, suggesting that driving experience supports flexible attention allocation *(Inagaki et al., 2020)*.

These results highlight that driver experience can strongly influences how LLN are used and perceived. Navigation interfaces should therefore consider differences in experience and cognitive capacity, supporting more effective attention allocation and information processing for diverse driver populations. For example, LLN could be provided as an optional feature that users can toggle on or off according to their preferences.

7.5 Limitations and Future Work

This study has several limitations that should be considered when interpreting the findings. First, the use of a low fidelity driving simulator with fixed motion base restricted the evaluation of lateral position measures (e.g., lane position, lane change), which are critical for understanding the effect of LLN on vehicle control and safety. The simulator's limited field of view and absence of peripheral vision may also have affected drivers' situational awareness and decision-making processes. However, the state-of-the-art simulator provided a controlled environment where navigation errors could be systematically induced and measured. This would not be feasible to achieve safely and ethically in real-world driving conditions.

Second, the study excluded several real-world navigation challenges, such as surrounding traffic, pedestrians, traffic signals, and environmental conditions, potentially simplifying the cognitive demands of navigation. However, this controlled setting was necessary to isolate the cognitive processes underlying navigation errors and to focus on the effects of the study's independent variables without the confounding influence of external factors. In addition, navigation errors categories (e.g., turning from or into the wrong lane, turning into the wrong direction on undivided roads) were excluded, as they were primarily influenced by limited haptic feedback and steering control challenges, rather than issues with navigational awareness. These exclusions, however, enabled focused analysis the most frequent and safety-critical navigation errors that LLN has potential to address.

Third, the study only examined the visual aspects of LLN. Auditory guidance, as an essential component of in-vehicle navigation, was deliberately excluded to isolate visual effects.

Looking forward, future research should validate these findings in higher-fidelity simulators or on-road studies to enhance ecological validity. Comparative studies are also needed to examine pure visual LLN guidance with multimodal approaches that combine auditory and visual cues. Further investigations should refine specific design elements of LLN, such as the optimal zoom level, timing of presentation, and intersection selection criteria, to maximize effectiveness. Additionally, our subgroup findings highlight the need for developing adaptive systems that tailor navigational information to different levels of driver experience and cognitive load. Importantly, HMI research should address the trade-offs between the navigational benefits and attentional costs of detailed navigation displays, aiming to design systems that are not only user-friendly but also prioritize safety.

8. Conclusion

This study systematically investigated the cognitive mechanisms underlying navigation errors and the effectiveness of lane-level navigation (LLN) in mitigating them. Through a comprehensive analysis of 64 navigation errors across 160 driving sessions, we developed a framework mapping observable navigation error to perception, interpretation, and decision-making failures. Our findings demonstrate that LLN significantly reduces interpretation failures and wrong turns, contributing to an overall 40% reduction in total navigation errors. Cognitive distraction increased workload and altered gaze behavior, which sometimes reduced LLN's effectiveness. However, these changes did not consistently lead to higher navigation error rates.

Crucially, these benefits were not uniform. Experienced drivers gained substantial navigation performance improvements and reported cognitive workload when using LLN. However, less experienced drivers experienced increased workload with limited benefits, highlighting the importance of considering driver experience in navigation system design.

Together, these findings advance understanding of the cognitive processes underlying navigation errors and provide evidence that LLN can improve performance under certain conditions. They also underscore the importance of designing adaptive navigation interfaces that tailor complexity to driver experience and situational demands, balancing navigational support with attentional costs.

References

Ahlström, C., Kircher, K., Nyström, M., & Wolfe, B. (2021). Eye Tracking in Driver Attention Research—How Gaze Data Interpretations Influence What We Learn. *Frontiers in Neuroergonomics*, *2*, 778043. https://doi.org/10.3389/fnrgo.2021.778043

Andrew Gelman & Jennifer Hill. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press.

Ayiei, A. (2020). The Use of Eye Tracking in Assessing Visual Attention. *Journal of Aircraft and Spacecraft Technology*, *4*(1), 117–124. https://doi.org/10.3844/jastsp.2020.117.124

Baldisserotto, F., Krejtz, K., & Krejtz, I. (2023). A Review of Eye Tracking in Advanced Driver Assistance Systems: An Adaptive Multi-Modal Eye Tracking Interface Solution. *2023 Symposium on Eye Tracking Research and Applications*, 1–3. https://doi.org/10.1145/3588015.3589512

Bauerfeind, K., Drüke, J., Schneider, J., Haar, A., Bendewald, L., & Baumann, M. (2021). Navigating with Augmented Reality – How does it affect drivers' mental load? *Applied Ergonomics*, *94*, 103398. https://doi.org/10.1016/j.apergo.2021.103398

Baumann, C., & Dierkes, K. (2023). *Neon Accuracy Test Report*. Pupil Labs. https://doi.org/10.5281/ZENODO.10420388

Betaille, D., & Toledo-Moreo, R. (2010). Creating Enhanced Maps for Lane-Level Vehicle Navigation. *IEEE Transactions on Intelligent Transportation Systems*, *11*(4), 786–798. https://doi.org/10.1109/TITS.2010.2050689

Bian, Y., Zhang, X., Wu, Y., Zhao, X., Liu, H., & Su, Y. (2021). Influence of prompt timing and messages of an audio navigation system on driver behavior on an urban expressway with five exits. *Accident Analysis & Prevention*, *157*, 106155. https://doi.org/10.1016/j.aap.2021.106155

Bryden, K. J., Charlton, J., Oxley, J., & Lowndes, G. (2023). Wayfinding Whilst Driving, Age and Cognitive Functioning. *Journal of Road Safety*, *34*(2), 22–37. https://doi.org/10.33492/JRS-D-18-00286

Burns, P. C. (1998). WAYFINDING ERRORS WHILE DRIVING. *Journal of Environmental Psychology*, *18*(2), 209–217. https://doi.org/10.1006/jevp.1998.0077

Cabrall, C. D. D., Janssen, N. M., & De Winter, J. C. F. (2018). Adaptive automation: Automatically (dis)engaging automation during visually distracted driving. *PeerJ Computer Science*, *4*, e166. https://doi.org/10.7717/peerj-cs.166

Castro, C. (Ed.). (2009). *Human factors of visual and cognitive performance in driving*. CRC Press.

Chen, S. (2024). Eye Tracking Technology in the Field of Intelligent Driving. *2024 Asia-Pacific Conference on Software Engineering, Social Network Analysis and Intelligent Computing (SSAIC)*, 786–790. https://doi.org/10.1109/SSAIC61213.2024.00159

Dalton, P., Agarwal, P., Fraenkel, N., Baichoo, J., & Masry, A. (2013). Driving with navigational instructions: Investigating user behaviour and performance. *Accident Analysis & Prevention*, *50*, 298–303. https://doi.org/10.1016/j.aap.2012.05.002

Ege, E. S., Cetin, F., & Basdogan, C. (2011a). Vibrotactile feedback in steering wheel reduces navigation errors during GPS-guided car driving. *2011 IEEE World Haptics Conference*, 345–348. https://doi.org/10.1109/WHC.2011.5945510

Ege, E. S., Cetin, F., & Basdogan, C. (2011b). Vibrotactile feedback in steering wheel reduces navigation errors during GPS-guided car driving. *2011 IEEE World Haptics Conference*, 345–348. https://doi.org/10.1109/WHC.2011.5945510

Endsley, M. R. (1988). Design and evaluation for situation awareness enhancement. *Human Factors Society 32nd Annual Meeting*, 97–101. https://doi-org.tudelft.idm.oclc.org/10.1177/154193128803200221

Endsley, M. R. (1999). Situation Awareness and Human Error: Designing to Support Human Performance. *Proceedings of the High Consequence Systems Surety Conference*, 2–9.

Engström, J., Markkula, G., Victor, T., & Merat, N. (2017). Effects of Cognitive Load on Driving Performance: The Cognitive Control Hypothesis. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *59*(5), 734–764. https://doi.org/10.1177/0018720817690639

Faschina, S., Stieglitz, R.-D., Muri, R., Strohbeck-Kühner, P., Graf, M., Mager, R., & Pflueger, M. O. (2021). Driving errors, estimated performance and individual characteristics under simulated and real road traffic conditions – A validation study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *82*, 221–237. https://doi.org/10.1016/j.trf.2021.07.018

Forbes, N., & Burnett, G. (2008). *Investigating the Contexts in which In- Vehicle Navigation System Users Have Received and Followed Inaccurate Route Guidance Instructions*.

Fu, R., Zhou, Y., Yuan, W., & Han, T. (2019). Effects of cognitive distraction on speed control in curve negotiation. *Traffic Injury Prevention*, *20*(4), 431–435. https://doi.org/10.1080/15389588.2019.1602769

Gardony, A. L., Hendel, D. D., & Brunyé, T. T. (2022). Identifying optimal graphical level of detail to support orienting with 3D geo-visualizations. *Spatial Cognition & Computation*, *22*(1–2), 135–160. https://doi.org/10.1080/13875868.2021.1892696

Guidetti, G., Guidetti, R., Manfredi, M., Manfredi, M., Lucchetta, A., & Livio, S. (2019). Saccades and driving. *Acta Otorhinolaryngologica Italica*, *39*(3), 186–196. https://doi.org/10.14639/0392-100X-2176

Inagaki, K., Maruno, T., & Yamamoto, K. (2020). Evaluation of EEG Activation Pattern on the Experience of Visual Perception in the Driving. *IEICE Transactions on Information and Systems*, *E103.D*(9), 2032–2034. https://doi.org/10.1587/transinf.2020EDL8020

International Organization for Standardization (ISO). (2020). *ISO 15007-1:2020 – Road vehicles—Measurement of driver visual behavior with respect to transport information and control systems—Part 1: Definitions and parameters*. ISO. https://www.iso.org/obp/ui/#iso:std:iso:15007:ed-1:v1:en

Jalayer, M., Zhou, H., & Zhang, B. (2016). Evaluation of navigation performances of GPS devices near interchange area pertaining to wrong-way driving. *Journal of Traffic and Transportation Engineering (English Edition)*, *3*(6), 593–601. https://doi.org/10.1016/j.jtte.2016.07.003

Kapitaniak, B., Walczak, M., Kosobudzki, M., Jóźwiak, Z., & Bortkiewicz, A. (2015). Application of eye-tracking in drivers testing: A review of research. *International Journal of Occupational Medicine and Environmental Health*, *28*(6), 941–954. https://doi.org/10.13075/ijomeh.1896.00317

Khattak, A. J., Ahmad, N., Wali, B., & Dumbaugh, E. (2021). A taxonomy of driving errors and violations: Evidence from the naturalistic driving study. *Accident Analysis & Prevention*, *151*, 105873. https://doi.org/10.1016/j.aap.2020.105873

Kidd, D. G., Tison, J., Chaudhary, N. K., McCartt, A. T., & Casanova-Powell, T. D. (2016). The influence of roadway situation, other contextual factors, and driver characteristics on the prevalence of driver secondary behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 1–9. https://doi.org/10.1016/j.trf.2016.06.004

Kircher, K., Kujala, T., & Ahlström, C. (2020). On the Difference Between Necessary and Unnecessary Glances Away From the Forward Roadway: An Occlusion Study on the Motorway. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *62*(7), 1117–1131. https://doi.org/10.1177/0018720819866946

Knapper, A., Christoph, M., Hagenzieker, M., & Brookhuis, K. (2015). Comparing a driving simulator to the real road regarding distracted driving speed. *European Journal of Transport and Infrastructure Research*. https://doi.org/10.18757/EJTIR.2015.15.2.3069

Kun, A. L., Paek, T., Memarović, N., & Palinko, O. (2009). *Glancing at Personal Navigation Devices Can Affect Driving: Experimental Results and Design Implications*.

Lee, J.-W., Yoon, C.-R., Kang, J., Park, B.-J., & Kim, K.-H. (2015). Development of lane-level guidance service in vehicle augmented reality system. *2015 17th International Conference on Advanced Communication Technology (ICACT)*, 263–266. https://doi.org/10.1109/ICACT.2015.7224799

Lin, C.-T., Wu, H.-C., & Chien, T.-Y. (2010). Effects of e-map format and sub-windows on driving performance and glance behavior when using an in-vehicle navigation system. *International Journal of Industrial Ergonomics*, *40*(3), 330–336. https://doi.org/10.1016/j.ergon.2010.01.010

Lin, P.-C., & Chen, S.-I. (2013). The effects of gender differences on the usability of automotive on-board navigation systems – A comparison of 2D and 3D display. *Transportation Research Part F: Traffic Psychology and Behaviour*, *19*, 40–51. https://doi.org/10.1016/j.trf.2013.03.001

Liu, B., Zhang, G., & Cui, Y. (2024). The Application of Eye Tracking Technology in Human-Machine Co-driving System under the Background of Intelligent Vehicle Development. *Proceedings of the 3rd International Conference on Art Design and Digital Technology, ADDT 2024, May 24–26, 2024, Luoyang, China*. Proceedings of the 3rd International Conference on Art Design and Digital Technology, ADDT 2024, May 24–26, 2024, Luoyang, China, Luoyang, People's Republic of China. https://doi.org/10.4108/eai.24-5-2024.2350120

Ma, R., & Kaber, D. B. (2007). Situation awareness and driving performance in a simulated navigation task. *Ergonomics*, *50*(8), 1351–1364. https://doi.org/10.1080/00140130701318913

Mehler, B., Reimer, B., & Dusek, J. A. (2011). *MIT AgeLab Delayed Digit Recall Task (n-back)*.

Meuleners, L., & Fraser, M. (2015). A validation study of driving errors using a driving simulator. *Transportation Research Part F: Traffic Psychology and Behaviour*, *29*, 14–21. https://doi.org/10.1016/j.trf.2014.11.009

Morris, N. L., Schwieters, K. R., Tian, D., & Craig, C. M. (2024). Evaluation of driver navigational errors and acceptance of a simulated J-turn intersection. *Accident Analysis & Prevention*, *198*, 107490. https://doi.org/10.1016/j.aap.2024.107490

Nakayama, M., Sun, Q. (Chayn), & Xia, J. (Cecilia). (2024). Car driving temporal cognitive workload estimation using features of eye tracking. *Proceedings of the 2024 Symposium on Eye Tracking Research and Applications*, 1–3. https://doi.org/10.1145/3649902.3655643

National Center for Statistics and Analysis. (2025). *Distracted Driving in 2023* (Research Note No. DOT HS 813 703). National Highway Traffic Safety Administration.

Navigation SDK for Automotive. (n.d.). [Computer software]. TomTom N.V. https://www.tomtom.com/products/navigation-sdk-for-automotive/

Niezgoda, M., Tarnowski, A., Kruszewski, M., & Kamiński, T. (2015). Towards testing auditory–vocal interfaces and detecting distraction while driving: A comparison of eye-movement measures in the assessment of cognitive workload. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 23–34. https://doi.org/10.1016/j.trf.2015.04.012

Nilsson, E. J., Aust, M. L., Engström, J., Svanberg, B., & Lindén, P. (2018). Effects of cognitive load on response time in an unexpected lead vehicle braking scenario and the detection response task (DRT). *Transportation Research Part F: Traffic Psychology and Behaviour*, *59*, 463–474. https://doi.org/10.1016/j.trf.2018.09.026

Nobukawa, S., Wagatsuma, N., & Inagaki, K. (2021). Gamma Band Functional Connectivity Enhanced by Driving Experience. *2021 IEEE 3rd Global Conference on Life Sciences and Technologies (LifeTech)*, 379–381. https://doi.org/10.1109/LifeTech52111.2021.9391852

Öztürk, İ., Merat, N., Rowe, R., & Fotios, S. (2023). The effect of cognitive load on Detection-Response Task (DRT) performance during day- and night-time driving: A driving simulator study with young and older drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *97*, 155–169. https://doi.org/10.1016/j.trf.2023.07.002

Palinko, O., Kun, A. L., Shyrokov, A., & Heeman, P. (2010). Estimating cognitive load using remote eye tracking in a driving simulator. *Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications - ETRA '10*, 141. https://doi.org/10.1145/1743666.1743701

Pan, Y., Zhang, Q., Zhang, Y., Ge, X., Gao, X., Yang, S., & Xu, J. (2022). Lane-change intention prediction using eye-tracking technology: A systematic review. *Applied Ergonomics*, *103*, 103775. https://doi.org/10.1016/j.apergo.2022.103775

Papantoniou, P., Yannis, G., & Christofa, E. (2019). Which factors lead to driving errors? A structural equation model analysis through a driving simulator experiment. *IATSS Research*, *43*(1), 44–50. https://doi.org/10.1016/j.iatssr.2018.09.003

Pinheiro, J. C., & Bates, D. M. (2000). *Mixed-Effects Models in Sand S-PLUS*. Springer New York. https://doi.org/10.1007/978-1-4419-0318-1

Read, K., Yu, L., Emerson, J., Dawson, J., Aksan, N., & Rizzo, M. (2011, June 30). Effects of Familiarity and Age on Driver Safety Errors During Wayfinding. *Driving Assessment Conference 2011*. Driving Assessment Conference 2011. https://doi.org/10.17077/drivingassessment.1448

Ringhand, M., Siebke, C., Bäumler, M., & Petzoldt, T. (2022). Approaching intersections: Gaze behavior of drivers depending on traffic, intersection type, driving maneuver, and secondary task involvement. *Transportation Research Part F: Traffic Psychology and Behaviour*, *91*, 116–135. https://doi.org/10.1016/j.trf.2022.09.010

Savage, S. W., Potter, D. D., & Tatler, B. W. (2020). The effects of cognitive distraction on behavioural, oculomotor and electrophysiological metrics during a driving hazard perception task. *Accident Analysis & Prevention*, *138*, 105469. https://doi.org/10.1016/j.aap.2020.105469

Schoemig, N., Heckmann, M., Wersing, H., Maag, C., & Neukum, A. (2018). "Please watch right" – Evaluation of a speech-based on-demand assistance system for urban intersections. *Transportation Research Part F: Traffic Psychology and Behaviour*, *54*, 196–210. https://doi.org/10.1016/j.trf.2018.01.018

Scott E. Maxwell, Harold D. Delaney, & Ken Kelley. (2018). *Designing Experiments and Analyzing Data: A Model Comparison Perspective*. Routledge.

Song, T., Capurso, N., Cheng, X., Yu, J., Chen, B., & Zhao, W. (2017). Enhancing GPS With Lane-Level Navigation to Facilitate Highway Driving. *IEEE Transactions on Vehicular Technology*, *66*(6), 4579–4591. https://doi.org/10.1109/TVT.2017.2661316

Strayer, D. L., Turrill, J., Cooper, J. M., Coleman, J. R., Medeiros-Ward, N., & Biondi, F. (2015). Assessing Cognitive Distraction in the Automobile. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(8), 1300–1324. https://doi.org/10.1177/0018720815575149

Suzuki, M., & Moriya, S. (2024). *A Study on Effect of Information from Navigation System on Driving Behavior*.

Uc, E. Y., Rizzo, M., Anderson, S. W., Sparks, J. D., Rodnitzky, R. L., & Dawson, J. D. (2007). Impaired navigation in drivers with Parkinson's disease. *Brain*, *130*(9), 2433–2440. https://doi.org/10.1093/brain/awm178

Ucar, S., Higuchi, T., & Altintas, O. (2023). Driver Support In Confusion Zones. *2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 1–6. https://doi.org/10.1109/MT-ITS56129.2023.10241714

Unity (Version 6000.0.23f1). (2024). [Computer software]. Unity Technologies. https://unity.com

Von Janczewski, N., Wittmann, J., Engeln, A., Baumann, M., & Krauß, L. (2021). A meta-analysis of the n-back task while driving and its effects on cognitive workload. *Transportation Research Part F: Traffic Psychology and Behaviour*, *76*, 269–285. https://doi.org/10.1016/j.trf.2020.11.014

Wen, S., Ping, S., Wang, J., Liang, H.-N., Xu, X., & Yan, Y. (2024). AdaptiveVoice: Cognitively Adaptive Voice Interface for Driving Assistance. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–18. https://doi.org/10.1145/3613904.3642876

Wilcoxon, F. (1945). Individual Comparisons by Ranking Methods. *Biometrics Bulletin*, *1*(6), 80. https://doi.org/10.2307/3001968

Winkler, M., & Soleimani, M. (2025). A Review of Augmented Reality Heads Up Display in Vehicles: Effectiveness, Application, and Safety. *International Journal of Human–Computer Interaction*, 1–16. https://doi.org/10.1080/10447318.2024.2443252

Wobbrock, J. O., Findlater, L., Gergle, D., & Higgins, J. J. (2011). The aligned rank transform for nonparametric factorial analyses using only anova procedures. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 143–146. https://doi.org/10.1145/1978942.1978963

Wood, J. M., Anstey, K. J., Lacherez, P. F., Kerr, G. K., Mallon, K., & Lord, S. R. (2009). The On-Road Difficulties of Older Drivers and Their Relationship with Self-Reported Motor Vehicle Crashes. *Journal of the American Geriatrics Society*, *57*(11), 2062–2069. https://doi.org/10.1111/j.1532-5415.2009.02498.x

Woollett, K., & Maguire, E. A. (2010). The effect of navigational expertise on wayfinding in new environments. *Journal of Environmental Psychology*, *30*(4), 565–573. https://doi.org/10.1016/j.jenvp.2010.03.003

Wynne, R. A., Beanland, V., & Salmon, P. M. (2019). Systematic review of driving simulator validation studies. *Safety Science*, *117*, 138–151. https://doi.org/10.1016/j.ssci.2019.04.004

Yang, L., Bian, Y., Zhao, X., Ma, J., Wu, Y., Chang, X., & Liu, X. (2021). Experimental research on the effectiveness of navigation prompt messages based on a driving simulator: A case study. *Cognition, Technology & Work*, *23*(3), 439–458. https://doi.org/10.1007/s10111-020-00645-w

Yang, S., Kuo, J., & Lenné, M. G. (2018). Analysis of Gaze Behavior to Measure Cognitive Distraction in Real-World Driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *62*(1), 1944–1948. https://doi.org/10.1177/1541931218621441

Yang, S., Wilson, K. M., Roady, T., Kuo, J., & Lenné, M. G. (2022). Evaluating Driver Features for Cognitive Distraction Detection and Validation in Manual and Level 2 Automated Driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *64*(4), 746–759. https://doi.org/10.1177/0018720820964149

Yared, T., Patterson, P., & All, E. S. A. (2020). Are safety and performance affected by navigation system display size, environmental illumination, and gender when driving in both urban and rural areas? *Accident Analysis & Prevention*, *142*, 105585. https://doi.org/10.1016/j.aap.2020.105585

Yared, T., Patterson, P., & Mumani, A. (2024). Distraction and visual search characteristics of young drivers when using navigation system displays. *Journal of Engineering Research*, *12*(3), 484–493. https://doi.org/10.1016/j.jer.2023.09.023

Yuen, N. H., Tam, F., Churchill, N. W., Schweizer, T. A., & Graham, S. J. (2021). Driving With Distraction: Measuring Brain Activity and Oculomotor Behavior Using fMRI and Eye-Tracking. *Frontiers in Human Neuroscience*, *15*, 659040. https://doi.org/10.3389/fnhum.2021.659040

Zang, L., & Liu, H. (2012). A Real-Time Video-based Eye Tracking Approach for Driver Attention Study. *Computing and Informatics*, *31*(4), 805–825.

Zhang, X., Bian, Y., Ou, J., Zhao, X., Huang, J., & Li, Y. (2024). Optimized Design of Driver-Assisted Navigation System for Complex Road Scenarios. *2024 IEEE Intelligent Vehicles Symposium (IV)*, 1915–1920. https://doi.org/10.1109/IV55156.2024.10588547

Zheng, L., Li, B., Yang, B., Song, H., & Lu, Z. (2019). Lane-Level Road Network Generation Techniques for Lane-Level Maps of Autonomous Vehicles: A Survey. *Sustainability*, *11*(16), 4511. https://doi.org/10.3390/su11164511

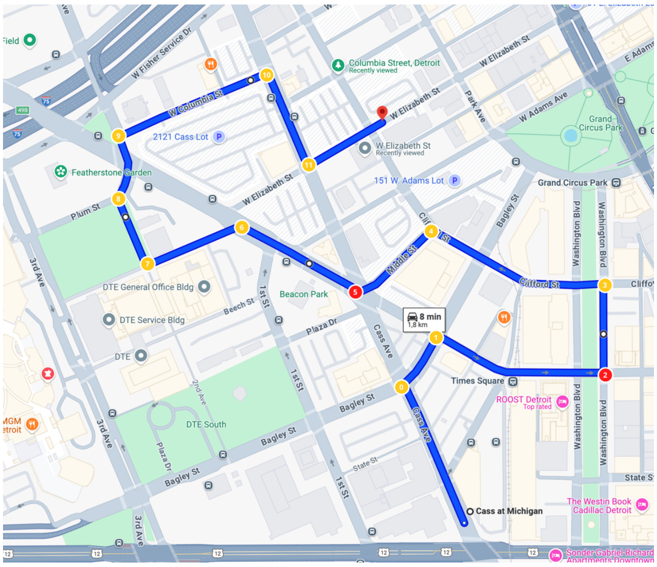
Zhong, Q., Zhi, J., Xu, Y., Gao, P., & Feng, S. (2024). Assessing driver distraction from in-vehicle information system: An on-road study exploring the effects of input modalities and secondary task types. *Scientific Reports*, *14*(1), 20289. https://doi.org/10.1038/s41598-024-71226-4

Appendices

Appendix A: Driving Routes

Route A spans 1.8 km, with 7 right turns and 5 left turns. Intersection A2 features two closed paths and intersection A5 features multiple roads intersected, which are designed to induce more navigation errors.

INT	Intended Action	Distance (m)
A0	Turn Right	198
A1	Turn Right	80
A2	Turn Left	200
A3	Turn Left	104
A4	Turn Left	228
A5	Turn Right	105
A6	Turn Left	170
A7	Turn Right	131
A8	Turn Right	90
A9	Turn Right	77
A10	Turn Right	195
A11	Turn Left	120



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Route B spans 1.9 km, with 7 right turns and 5 left turns. Intersection B5 and B9 feature multiple roads intersected, which are designed to induce more navigation errors.

INT	Intended Action	Distance (m)
B0	Turn Right	176
B1	Turn Right	196
B2	Turn Right	129
B3	Turn Left	57
B4	Turn Left	107
B5	Turn Right	195
B6	Turn Right	128
B7	Turn Left	167
B8	Turn Right	151
B9	Bear Left	96
B10	Turn Right	226
B11	Turn Left	124

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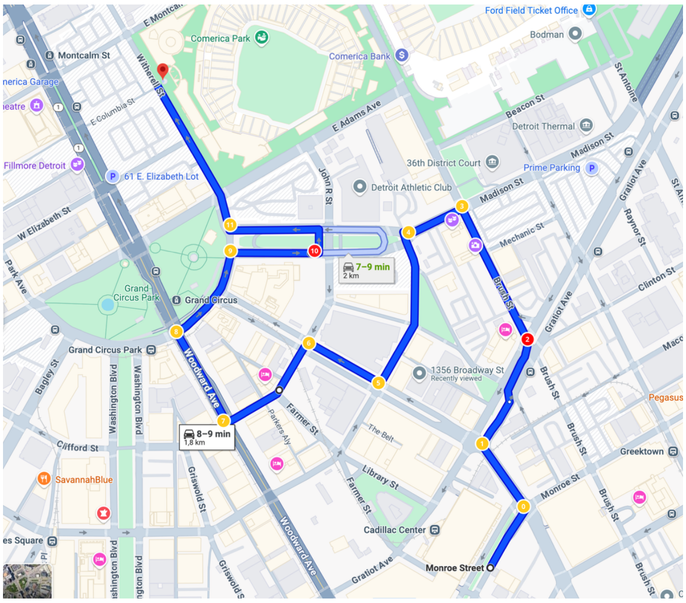
Route C spans 1.8 km, with 6 right turns, 5 left turns and 1 U-turn. Intersection C2 and C10 feature multiple closed paths, which are designed to induce more navigation errors.

INT	Intended Action	Distance (m)
C0	Turn Left	229
C1	Turn Right	93
C2	Turn Left	139
C3	Turn Left	193
C4	Turn Left	78
C5	Turn Right	203
C6	Turn Left	106
C7	Turn Right	140
C8	Turn Right	129
C9	Turn Right	123
C10	U-Turn	125
C11	Turn Right	129



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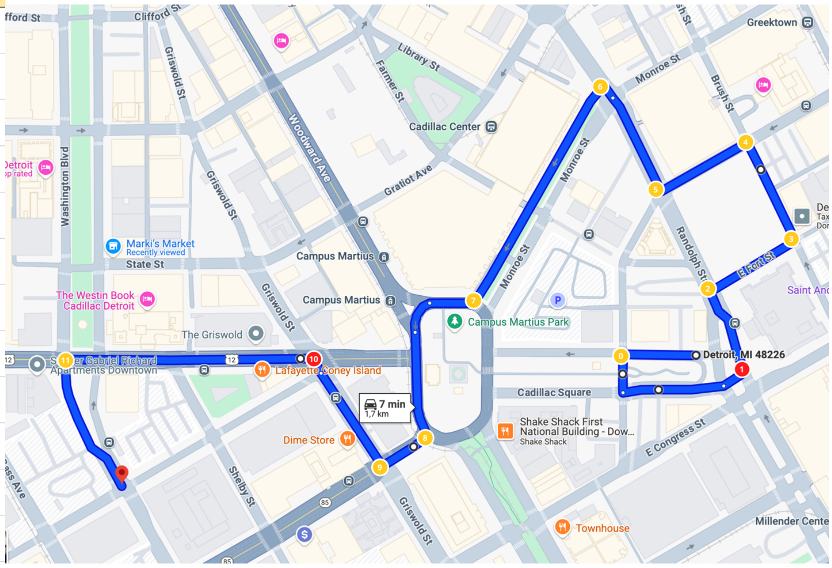
Route D spans 1.7 km, with 4 right turns, 7 left turns and 1 U-turn. Intersection D1 features two closed paths and intersection D10 features multiple roads intersected, which are designed to induce more navigation errors.

INT	Intended Action	Distance (m)
D0	U-Turn	79
D1	Turn Left	120
D2	Turn Right	96
D3	Turn Left	89
D4	Turn Left	99
D5	Turn Right	86
D6	Turn Left	117
D7	Turn Right	237
D8	Turn Right	180
D9	Turn Left	49
D10	Turn Left	115
D11	Turn Left	242



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Appendix B: Informed Consent Form

Study Title: Eye-tracking to understand Navigation Behaviors

Researcher: Xuerong Cai, MSc Student, TU Delft Faculty of Industrial Design Engineering
Collaborating Organization: TomTom B.V.

You are being invited to participate in a research study titled ***Eye-tracking to understand Navigation Behaviors***. This study is being done by ***Xuerong Cai*** from the TU Delft, in collaboration with TomTom.

The purpose of this research study is **to investigate how different types of navigation display, and the presence of cognitive distractions influence navigation behaviour and decision-making while driving.** Your participation will take approximately **30 minutes**. The data will be used for scientific publications, master's thesis evaluation, presentations, and potentially to inform future navigation interface development by TomTom.

We will be asking you to drive in a simulator equipped with a navigation display and eye-tracking device, follow turn-by-turn instructions, and complete occasional cognitive tasks (2-back test), as well as fill out short questionnaires about your experience after each simulated route.

As with any online activity the risk of a breach is always possible. To the best of our ability your answers in this study will remain confidential. All collected data will be de-identified and anonymized, stored on secure encrypted servers at TU Delft, and access to raw data will be restricted to the research team. As part of TU Delft's Open Science commitment, certain de-identified datasets—including eye-tracking recordings and simulator logs—will be made publicly available in institutional repository or paper publication. No personally identifiable information will be included in any publicly shared dataset.

Your participation in this study is entirely voluntary, and you can withdraw at any time. You are free to omit any questions. Note that once anonymized data is aggregated into group results, it will no longer be possible to remove your specific data.

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICPANT TASKS AND VOLUNTARY PARTICIPATION		
1. I have read and understood the study information dated [*DD/MM/YYYY*], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	☐	☐
2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions, and I can withdraw from the study at any time, without having to give a reason. I understand that I may request the deletion of my data up to **21 calendar days** after my session. I will be reminded of this deadline by email after participation. After this 21-day period, my data will be anonymized and/or aggregated, and it will no longer be possible to identify or remove my individual data from the dataset.	☐	☐
3. I understand that taking part in the study involves: driving in a simulator, while my eye movements and driving performance are recorded; wearing an eye-tracker (Pupil Labs Neon); responding to brief cognitive tasks (2-back); and completing short self-report questionnaires (NASA-TLX, UEQ, and error reflection).	☐	☐
4. I understand that the study will end when I have completed all four simulated driving conditions, lasting approximately 30 minutes in total.		
B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		
5. I understand that potential risks include mild visual fatigue or discomfort from the simulator or eye-tracker, which can be mitigated by taking breaks or stopping the session.	☐	☐
6. I understand that taking part in the study also involves collecting specific personally identifiable information (PII): email contact for scheduling (not linked to data) and personally identifiable research data (PIRD): eye movement recordings, simulator video recordings. There is a minimal risk of identity re-identification, which will be mitigated through strict data management.	☐	☐
7. I understand that the following steps will be taken to minimize the threat of a data breach: pseudonymization, encrypted file storage, restricted access to raw recordings, and de-identification of all data before analysis.	☐	☐
8. I understand that personal information collected about me that can identify me, such as my email or visual data, will not be shared beyond the research team.	☐	☐
9. I understand that the identifiable personal data I provide will be destroyed: at the end of the study after final analysis and publication, or no later than 12 months after data collection is complete.	☐	☐
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
10. I understand that after the research study the de-identified information I provide will be used for: scientific journal publications, Master's thesis defense, conference presentations, and may inform interface or product development by TomTom.	☐	☐
11. I agree that my responses, views or other input can be quoted anonymously in research outputs.	☐	☐
D: (LONGTERM) DATA STORAGE, ACCESS AND REUSE		
12. I give permission for the de-identified eye-tracking data, driving behaviour logs, simulator video recordings, and questionnaire responses that I provide to be archived in TU Delft's open-access research data repository, and used in public thesis publications, academic presentations, and future research and teaching.	☐	☐
13. I understand that access to this repository is open to the public, in accordance with TU Delft's Open Science policy. No personally identifiable information will be shared, and all data will be de-identified before being made accessible.	☐	☐

Signatures

____________________________	____________________________	_________
Name of participant [printed]	Signature	Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_Xuerong Cai_______________	____________________	_02-05-2025____
Researcher name [printed]	Signature	Date

Appendix C: NASA-LTX Questionnaire

How do you feel about the **driving task** completed just now?

Answer by a scale from 1 (Very Low) to 21 (Very High)

- How mentally demanding was the task?
- How physically demanding was the task?
- How hurried or rushed was the pace of the task?
- How successful were you in accomplishing what you were asked to do?
- How hard did you have to work to accomplish your level of performance?
- How insecure, discouraged, irritated, stressed and annoyed were you?

Appendix D: User Experience Questionnaire

How do you feel about the **navigation system** during the driving session?

Answer by a scale from 1 (Negative) to 7 (Positive)

- Obstructive/Supportive
- Complicated/Easy
- Inefficient/Efficient
- Confusing/Clear
- Boring/Exciting
- Not interesting/Interesting
- Conventional/Inventive
- Usual/Leading Edge

Appendix E: Error Report Questionnaire

1. Can you recall making any mistakes following the planned route during this drive?
- Yes, I missed a turn
- Yes, I made a wrong turn
- Yes, I made a risky/ abrupt turn
- Yes, I drove on wrong way
- Yes, something else (please specify)
- No
2. What do you think caused the mistake?
- I didn’t notice the upcoming intersection or turning instruction
- I misunderstood the turning instruction
- I understood everything but acted too late or wrongly
- I’m not used to driving in the simulator
- Other reason (please specify)

Appendix F: Eye-Tracking Metrics

Eye-tracking data was recorded using a Pupil Labs Neon wearable eye-tracker at 200 Hz and processed using Pupil Labs software and custom Python scripts. The following metrics were calculated:

General Event Identification

Fixations, Saccades, and Blinks: These events were identified from raw gaze data using the default algorithms and parameters within the Pupil Labs software.

Areas of Interest (AOIs): Gaze data was mapped to two primary AOIs: the navigation screen and the forward road view.

Fixation Metrics (per AOI)

Fixation Rate (fixations/s): The number of fixations occurring per second within an AOI.

Percent Time Fixating (%): The percentage of the total session time that the participant spent fixating within an AOI.

Average Fixation Duration (ms): The mean duration of individual fixations within an AOI.

Fixation Position Variance (normalized): The mean variance of normalized X and Y fixation coordinates on an AOI, indicating the spread of visual attention.

Fixation Count Percent (%): The percentage of fixations within an AOI among all the fixations during a session.

Saccade Metrics

Saccade Rate (saccades/s): The total number of saccades per second.

Average Saccade Duration (ms): The mean duration of a saccade.

Average Saccade Amplitude (degrees): The mean angular distance covered by a saccade.

Average Saccade Velocity (pixels/s): The mean velocity of saccades.

Gaze & Glance Metrics

Gaze Rate (gaze points/s): The number of raw gaze points recorded per second within an AOI.

Glance Ratio (ratio): The ratio of total time spent fixating on the road versus the navigation display (Time fixating on road (%) / Time fixating on navigation (%)).

Pupil and Blink Metrics

Blink Rate (blinks/s): The number of blinks detected per second.

Average Pupil Diameter (mm): The mean pupil diameter, averaged from both eyes, as an indicator of cognitive load.

Pupil Diameter SD (mm): The standard deviation of the pupil diameter.

Appendix G: Driving Behavior Metrics

Driving data was logged by the Unity simulation and processed using custom Python scripts. The following metrics were calculated:

Vehicle Control

Mean Speed (kph) and **Speed SD (kph)**: The mean and standard deviation of driving speed (SpeedKph).

Mean Throttle and **Throttle SD (unitless)**: The mean and standard deviation of throttle input (Throttle).

Mean Acceleration (m/s^2) and **Acceleration SD (m/s^2)**: The mean and standard deviation of acceleration (Acceleration).

Lane keeping

Standard Deviation of Lane Position (SDLP) (meters): The standard deviation of the LaneDeviation data, a measure of weaving.

Mean Lane Deviation (meters): The mean of the absolute LaneDeviation values from the lane center.

Max Absolute Lane Deviation (meters): The maximum absolute deviation from the lane center.

Steering Behavior

Steering SD (unitless): The standard deviation of the raw steering wheel input (SteerInput).

Steering Reversal Rate (reversals/min): The frequency of corrective steering adjustments, calculated as the number of steering direction changes per minute.

Sudden Steering Changes (count): The number of instances where the absolute change in steering input between consecutive frames exceeded the session's 95th percentile for that value.

Safety & Error Events

Braking Count (count): The number of data frames where the brake pedal was engaged (Brake > 0).

Wrong Way Duration (seconds): The total time spent in lanes flagged as wrong way (lane meant for opposite traffic).

IDE Master Graduation Project

Project team, procedural checks and Personal Project Brief

In this document the agreements made between student and supervisory team about the student's IDE Master Graduation Project are set out. This document may also include involvement of an external client, however does not cover any legal matters student and client (might) agree upon. Next to that, this document facilitates the required procedural checks:

- Student defines the team, what the student is going to do/deliver and how that will come about
- Chair of the supervisory team signs, to formally approve the project's setup / Project brief
- SSC E&SA (Shared Service Centre, Education & Student Affairs) report on the student's registration and study progress
- IDE's Board of Examiners confirms the proposed supervisory team on their eligibility, and whether the student is allowed to start the Graduation Project

STUDENT DATA & MASTER PROGRAMME

Complete all fields and indicate which master(s) you are in

Family name: Cai 7644

Initials: X.

Given name: Xuerong

Student number: 5614392

IDE master(s): IPD ☐ DfI ☑ SPD ☐

2nd non-IDE master:

Individual programme *(date of approval)*:

Medisign ☐

HPM ☐

SUPERVISORY TEAM

Fill in he required information of supervisory team members. If applicable, company mentor is added as 2nd mentor

Chair: Evangelos Niforatos — dept./section: Sustainable Design Engineering

mentor: Tianhao He — dept./section: Sustainable Design Engineering

2nd mentor: Harry Haladjian

client: TomTom

city: Amsterdam — country: Netherlands

optional comments:

! Ensure a heterogeneous team. In case you wish to include team members from the same section, explain why.

! Chair should request the IDE Board of Examiners for approval when a non-IDE mentor is proposed. Include CV and motivation letter.

! 2nd mentor only applies when a client is involved.

APPROVAL OF CHAIR on PROJECT PROPOSAL / PROJECT BRIEF -> to be filled in **by the Chair** of the supervisory team

Sign for approval (Chair)

Evangelos Niforatos Digitally signed by Evangelos Niforatos Date: 2025.03.31 21:17:16 +02'00'

Name: Evangelos Niforatos Date: 31/03/2025 Signature

DESIGN FOR our future

TU Delft

Personal Project Brief – IDE Master Graduation Project

Name student Xuerong Cai

Student number 5614392

PROJECT TITLE, INTRODUCTION, PROBLEM DEFINITION and ASSIGNMENT

Complete all fields, keep information clear, specific and concise

Project title Gaze-Driven Navigation for Driving Assistance

Please state the title of your graduation project (above). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.

Introduction

Describe the context of your project here; What is the domain in which your project takes place? Who are the main stakeholders and what interests are at stake? Describe the opportunities (and limitations) in this domain to better serve the stakeholder interests. (max 250 words)

This project explores how driver gaze behavior can predict navigation errors and how adaptive HMI can assist drivers in preventing mistakes. The research takes place in collaboration with TomTom, a navigation and mapping technology company with interest in enhancing navigation experience and safety through intelligent map.

Background context:
(1) Real-time eye-tracking technology is being used in Advanced Driver Distraction Warning System, which is mandatory for all new production vehicles by 2026 according to European General Safety Regulation. This opens up the opportunity to use in-vehicle gaze data to understand driver status and improve navigation experience accordingly.
(2) Extensive research has explored driver attention patterns using eye-tracking data. However, there is a notable gap in identifying specific gaze behaviors that precede navigation errors.
(3) As in-vehicle navigation systems continue to advance, eye-tracking offers a powerful tool to analyze how drivers interact with maps and HMI systems.

Based on these opportunities, this project aims to improve and evaluate real-time driver assistance by integrating eye-tracking data into human-machine interaction system. Specifically, the focus will be on driver confusion or distraction that leads to navigation errors under complex road conditions.

➔ *space available for images / figures on next page*

introduction (continued): space for images

click to add picture

image / figure 1

image / figure 2

Personal Project Brief – IDE Master Graduation Project

Problem Definition

What problem do you want to solve in the context described in the introduction, and within the available time frame of 100 working days? (= Master Graduation Project of 30 EC). What opportunities do you see to create added value for the described stakeholders? Substantiate your choice.
(max 200 words)

Drivers often misinterpret navigation guidance, become distracted, or hesitate at complex road conditions, leading to missed turns, last-minute maneuvers, or navigation errors. These issues reduce driving efficiency and even threaten safety. Current navigation systems do not take into account the driver attention levels, making guidance static rather than adaptive.

In this project, I aim to identify gaze patterns associated with navigation errors and evaluate how adaptive HMI interventions can proactively assist drivers. This will be achieved by (1)analyzing gaze behaviour before errors made and (2)designing and testing a prototype navigation interface in a simulated driving environment using eye-tracking technology.

This research presents an opportunity to bridge human perception and navigation system intelligence, in order to improve driver interaction with digital maps.

Assignment

This is the most important part of the project brief because it will give a clear direction of what you are heading for. Formulate an assignment to yourself regarding what you expect to deliver as result at the end of your project. (1 sentence) As you graduate as an industrial design engineer, your assignment will start with a verb (Design/Investigate/Validate/Create), and you may use the green text format:

Investigate gaze-based indicators of navigation errors and design an adaptive HMI to improve navigation accuracy for drivers in a simulated driving environment.

Then explain your project approach to carrying out your graduation project and what research and design methods you plan to use to generate your design solution (max 150 words)

To achieve the research objectives, I will conduct a two-phase experiment:

1. Behavior Modeling:
- Collect eye-tracking data from drivers in a Unity-based driving simulator.
- Identify gaze behaviors (e.g., fixation patterns, saccades) correlated with navigation errors (e.g., missed turns).
- Analyze data using Python/MATLAB with support from university researchers.

2. HMI Adaptation Study:
- Develop an adaptive (visual) navigation interface that responds to detected confusion or distraction.
- Evaluate its effectiveness by comparing error rates and gaze behavior before and after intervention.

Research methods include eye-tracking analysis, user testing, and statistical modeling. The driving simulation provides a controlled but realistic test environment, ensuring insights are transferable to real-world scenarios.

Project planning and key moments

*To make visible how you plan to spend your time, you must make a planning for the full project. You are advised to use a Gantt chart format to show the different phases of your project, deliverables you have in mind, meetings and in-between deadlines. Keep in mind that all activities should fit within the given run time of 100 working days. Your planning should include a **kick-off meeting**, **mid-term evaluation meeting**, **green light meeting** and **graduation ceremony**. Please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any (for instance because of holidays or parallel course activities).*

Make sure to attach the full plan to this project brief.
The four key moment dates must be filled in below

Kick off meeting 2025-3-18

Mid-term evaluation 2025-5-16

Green light meeting 2025-7-29

Graduation ceremony 2025-8-26

In exceptional cases (part of) the Graduation Project may need to be scheduled part-time. Indicate here if such applies to your project

Part of project scheduled part-time	✔
For how many project weeks	2
Number of project days per week	1

Comments:
Break after mid-term evaluation

Motivation and personal ambitions

Explain why you wish to start this project, what competencies you want to prove or develop (e.g. competencies acquired in your MSc programme, electives, extra-curricular activities or other).

Optionally, describe whether you have some personal learning ambitions which you explicitly want to address in this project, on top of the learning objectives of the Graduation Project itself. You might think of e.g. acquiring in depth knowledge on a specific subject, broadening your competencies or experimenting with a specific tool or methodology. Personal learning ambitions are limited to a maximum number of five.
(200 words max)

I am particularly excited about using real driver behavior data to inform and validate design decisions. This project allows me to work across human behavior study, eye-tracking technology and data driven design—ensuring my design solutions are not just intuitive but scientifically backed. This aligns with my ambition to create more intelligent and “natural” navigation systems, making driving both safer and more intuitive.

Through this project, I aim to grow in the following ways:

1. Working with complex, real-world data: learning to collect and analyze human behavior data, drawing meaningful conclusions from it that can be applied to improve design.
2. Experimental research design: designing and conducting a structured study that leads to meaningful, validated conclusions.
3. Eye-tracking research: Gaining hands-on experience with eye-tracking technology and understanding its application in HMI.
4. Adaptive UI development: Exploring design towards dynamic interfaces based on real-time user states, that leads to more natural and individualized way of interaction.